

Exhibit KK

Exhibit E-21

**Invalidity of U.S. Patent No. 7,725,253 (“253 Patent”) Under Pre-AIA Section 102 or Section 103 in view of
Gregory Welch, SCAAT: Incremental Tracking with Incomplete Information (October 1996) (Ph.D. dissertation, Univ. of N.C. at
Chapel Hill) (on file with Dept. of Comp. Sci., Univ. of N.C.) (“Welch Thesis”)¹**

Welch Thesis was publicly available as early as than May 24, 1997. Plaintiffs belatedly asserted a priority date of June 13, 2001 for the ’253 Patent on December 22, 2021, 71 days after the Court’s deadline. Defendants have reviewed Plaintiffs’ alleged evidence of the purported June 13, 2001 priority date, and maintain that the ’253 Patent is not entitled to this priority date. See Defendants’ March 15, 2022 Supplemental Invalidity Contentions. Defendants reserve their objections to Plaintiffs’ belated assertion of the new priority date and expressly reserve all rights to challenge this alleged new priority date. As such, Defendants assume for the sake of these invalidity contentions, that the priority date for the ’253 Patent is August 9, 2002 based on the first filed Provisional Application from which the ’253 Patent claims priority. (Defendants do not concede nor agree that Plaintiffs are even entitled to this date.) Assuming this priority date, Welch Thesis qualifies as prior art under at least pre-AIA Section 102(a) and (b) to the ’253 Patent.

As described herein, the asserted claims of the ’253 Patent are invalid (a) under one or more sections of 35 U.S.C. § 102 as anticipated expressly or inherently by Welch Thesis (including the documents incorporated into Welch Thesis by reference) and (b) under 35 U.S.C. § 103 as obvious in view of Welch Thesis standing alone and, additionally, in combination with the knowledge of one of ordinary skill in the art, and/or other prior art, including but not limited to the prior art identified in Defendants’ Invalidity Contentions and the prior art described in the claim charts attached in Exhibits E-1 – E-23. With respect to the proposed modifications to Welch Thesis, as of the priority date of the ’253 Patent, such modification would have been obvious to try, an obvious combination of prior art elements according to known methods to yield predictable results, a simple substitution of one known element for another to obtain predictable results, a use of known techniques to improve a similar device or method in the same way, an application of a known technique to a known device or method ready for improvement to yield predictable results, a variation of a known work in one field of endeavor for use in either the same field or a different one based on design incentives or other market forces with variations that are predictable to one of ordinary skill in the art, and/or obvious in view of teachings, suggestions, and motivations in the prior art that would have led one of ordinary skill to modify or combine the prior art references.

¹ Discovery in this case is ongoing and, accordingly, this invalidity chart is not to be considered final. Defendants have conducted the invalidity analysis herein without having fully undergone claim construction and a *Markman* hearing. By charting the prior art against the claim(s) herein, Defendants are not admitting nor agreeing to Plaintiffs’ interpretation of the claims at issue in this case. Additionally, these charts provide representative examples of portions of the charted references that disclose the indicated limitations under Plaintiffs’ application of the claims; additional portions of these references other than the representative examples provided herein may also disclose the indicated limitation(s) and Defendants contend that the asserted claim(s) are invalid in light of the charted reference(s) as a whole. Defendants reserve the right to rely on additional citations or sources of evidence that also may be applicable, or that may become applicable in light of claim construction, changes in Plaintiffs’ infringement contentions, and/or information obtained during discovery as the case progresses. Further, by submitting these invalidity contentions, Defendants do not waive and hereby expressly reserve their right to raise other invalidity defenses, including but not limited to defenses under Sections 101 and 112. Defendants reserve the right to amend or supplement this claim chart at a later date, including after the Court’s order construing disputed claim terms.

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All cross-references should be understood to include material that is cross-referenced within the cross-reference. Where a particular figure is cited, the citation should be understood to encompass the caption and description of the figure as well as any text relating to or describing the figure. Conversely, where particular text referring to a figure is cited, the citation should be understood to include the figure as well.

A. INDEPENDENT CLAIM 1

CLAIM 1	Welch Thesis
[1.pre] A tracking system comprising:	<p>At least under Plaintiffs' apparent infringement theory, Welch Thesis discloses, either expressly or inherently, a method for tracking an object.</p> <p>No party has yet asserted that the preamble is limiting, nor has the Court construed the preamble as limiting. However, to the extent that the preamble is limiting, it is disclosed by Welch Thesis.</p> <p>In the alternative, this element would be obvious over Welch Thesis in light of the other references disclosed in Defendants' Invalidity Contentions and/or the knowledge of one of ordinary skill in the art.</p> <p><i>See, e.g.:</i></p> <p>The Kalman filter provides a powerful mathematical framework within which a minimum mean-square-error estimate of a user's position and orientation can be tracked using a sequence of single sensor observations, as opposed to groups of observations. We refer to this new approach as single-constraint-at-a-time or SCAAT tracking. The method improves accuracy by properly assimilating sequential observations, filtering sensor measurements, and by concurrently autocalibrating mechanical or electrical devices. The method facilitates user motion prediction, multisensor data fusion, and in systems where the observations are only available sequentially it provides estimates at a higher rate and with lower latency than a multiple-constraint approach.</p> <p>Welch Thesis at Abstract.</p> <p>The most significant aspect of this work is the introduction and exploration of the SCAAT approach to 3D tracking for virtual environments. However I also believe that this work may prove to be of interest to the larger scientific and engineering community in addressing a more general class of tracking and estimation problems.</p> <p>Welch Thesis at Abstract.</p>

Exhibit E-21

CLAIM 1	Welch Thesis
	<p><i>See also</i> Welch Thesis, Chapter 1.3 (describing how SCAAT is an “unusual approach to tracking”); Chapter 2.1 (describing the use of Kalman filters “in the context of tracking or navigation”); Chapter 4.3 (describing how the SCAAT algorithm is used for tracking); Chapter 7.7 (describing “other tracking implementations” for the SCAAT algorithm).</p> <p><i>See also</i> Defendants’ Invalidity Contentions for further discussion.</p>
[1.a] an estimation subsystem; and	<p>At least under Plaintiffs’ apparent infringement theory, Welch Thesis discloses, either expressly or inherently, an estimation subsystem. In the alternative, this element would be obvious over Welch Thesis in light of the other references disclosed in Defendants’ Invalidity Contentions and/or the knowledge of one of ordinary skill in the art.</p> <p><i>See, e.g.:</i></p> <p>A Kalman filter can be used to estimate a globally-observable process by sequentially incorporating only measurements of locally-unobservable processes. The use of a Kalman filter in such a manner offers several advantages: (1) a flexible framework for heterogeneous multisensor data fusion; (2) a unique opportunity to perform concurrent device autocalibration; and in a system that allows only sequential measurements, (3) significantly improved estimate rates and latencies; and (4) avoidance of the incorrect simultaneity assumption. Welch Thesis at 43.</p> <p>The Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) means of using noisy measurements to estimate the state of a linear system, while minimizing the expected mean-squared estimation error.</p> <p>Welch Thesis at 45.</p> <p>The SCAAT method represents an unusual approach to Kalman filter based multisensor data fusion. Because the filter operates on single sensor measurements, new estimates can be computed as soon as measurements from an individual sensor of any type become available, in virtually any order, and at any (possibly varying) rate. Such flexibility allows measurements from any combination of devices to be interlaced in the most convenient and expeditious fashion, ensuring that each estimate is computed from the most recent data offered by any combination of devices. The information from the various observations can then be blended using either a single SCAAT KF with multiple measurement models, or separate SCAAT filters (and thus statistics) each with single measurement models, in which case the estimates from the</p>

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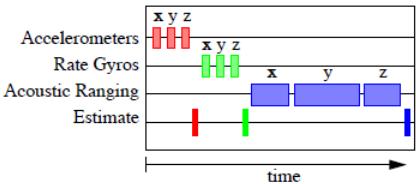
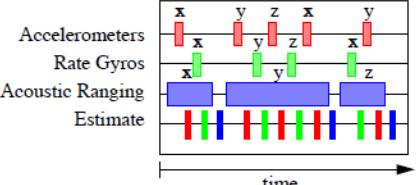
CLAIM 1	Welch Thesis
	<p>various models can be blended using a statistical multi-model approach (see for example [Bar-Shalom93]). Welch Thesis at 56-57.</p> <p>For the sake of illustration, imagine an inertial-acoustical hybrid tracking system composed of three accelerometers, three rate gyros, and an acoustical line-of-sight system (to control drift from the inertial sensors). Note that not only will the acoustical measurements take longer than the inertial measurements, the acoustical measurement times will vary with distance between the source and sensors. A conventional method for data fusion might repeat the fixed pattern shown in figure 2.7. Notice that an estimate is produced only after collecting an orthogonal group of measurements from each (any one) subsystem.</p>  <p>Figure 2.7: Timing diagram for a hypothetical conventional hybrid tracking system. The state estimate is updated only after each group of 3 homogeneous measurements.</p> <p>In contrast, a SCAAT implementation might interleave sensor measurements as depicted in figure 2.8. Note the flexibility of measurement type, availability, rate, and ordering. Again because an estimate is produced with every sensor measurement, latency is reduced and the estimation rate is increased.</p>  <p>Figure 2.8: Timing diagram for a SCAAT inertial-acoustical hybrid tracking system. The state estimate is updated whenever an individual measurement becomes available.</p> <p>Welch Thesis at 57-58.</p>

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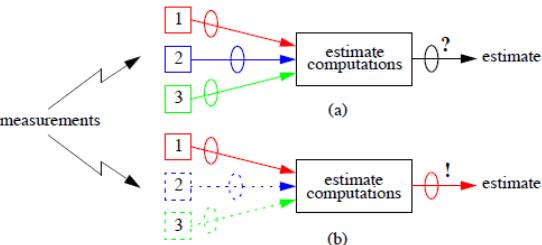
CLAIM 1	Welch Thesis
	<p>On the other hand, because the SCAAT method generates a new tracking estimate with each individual measurement, individual device imperfections are more readily identified. Furthermore, because the simultaneity assumption is avoided, the motion restrictions discussed in section 2.3.2 are removed, and autocalibration can be performed while concurrently tracking a target under normal conditions. The specific autocalibration method is presented in chapter 4, with experimental results in chapter 6.</p> <p>Welch Thesis at 61.</p>  <p>Figure 2.11: Autocalibration and attribution of measurement error. (a) Most algorithms operate on multiple measurements as a group, hence uncertainty or error (represented by the ellipses) in the final estimates is difficult to attribute to any individual sensor. (b) With the SCAAT method, uncertainty in final estimates can more easily be attributed to a particular individual sensor.</p> <p>Welch Thesis at 62.</p> <p>The tracking system that I employ in my experiments is an “inside-looking-out” optoelectronic system designed for interactive computer graphics or virtual environments. The system, which we call the “HiBall tracker”, is an improved version of the wide-area system described in [Ward92]. In these systems, user-mounted optical sensors observe infrared light-emitting diodes (LEDs) or beacons mounted in the ceiling above the user. The locations of the beacons are known (to some degree) so observations of them can be used to estimate the user’s position and orientation.</p> <p>Welch Thesis at 191.</p>

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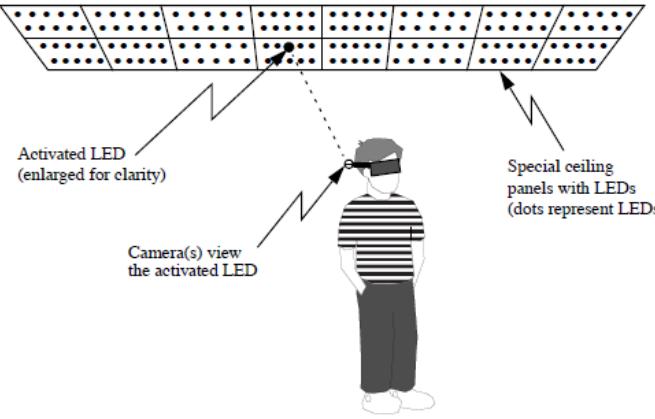
CLAIM 1	Welch Thesis
	 <p data-bbox="544 665 1199 736">Figure D.1: An outward-looking optoelectronic tracking system. User-mounted cameras look outward (generally upward) at active beacons in the environment.</p> <p data-bbox="502 757 777 789">Welch Thesis at 191.</p> <p data-bbox="502 829 1991 1046">One goal of the HiBall system is to provide a user with <i>wide-area</i> tracking. To this end, the LEDs are installed in special ceiling panels that replace standard-size acoustic ceiling tiles. (See figure D.1.) These tiles can be installed over a large area, thus providing a large working area. In fact, the current UNC installation consists of enough ceiling tiles to cover an area of approximately 5x5 meters, with a corresponding total of over 3,000 LEDs. The LED positions in world coordinates are initially estimated based on the ceiling panel design, which has them installed in a regular two-dimensional grid.</p> <p data-bbox="502 1083 1945 1225">The LEDs are connected to special circuit boards that are mounted on (above) the ceiling tiles, and these circuit boards are then connected to a computer. Thus LEDs can be individually activated under computer control as needed for the SCAAT observations. (The ceiling circuitry allows beacon activation at over 5000 LEDs per second.)</p> <p data-bbox="502 1230 777 1263">Welch Thesis at 192.</p> <p data-bbox="502 1302 1991 1405">In the original system described by [Ward92] the user wore a relatively large head-mounted mechanical fixture that supported several individually self-contained optical sensors or “cameras” and a backpack that contained the necessary signal processing and A/D conversion circuitry as shown in figure D.2.</p>

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	<p>In the new system the camera fixture and backpack in figure D.2 are together replaced by a relatively small sensor cluster called the HiBall. Figure D.3 is a picture of an unpopulated HiBall with a golf ball to convey a notion of size.</p> <p>A populated HiBall contains six lenses, six photodiodes with infrared filters, and all of the necessary circuitry for signal processing, A/D conversion, control, and high-speed serial communication. It is designed so that each photodiode can view infrared beacons (LEDs in this case) through each of several adjacent lenses, thus implementing up to 26 distinct infrared cameras.</p> <p>The photodiodes provide four signals that together indicate the position of the centroid of light (infrared in this case) as it appears on the two-dimensional photodiode surface. At any point in time, the internal A/D conversion circuitry can sample these signals for any one photodiode. These samples would then be sent to an external computer via a high-speed serial link where they would be converted to the measurement that reflect the position of the image of the infrared beacon on the two-dimensional photodiode.</p> <p>If the photodiode measurements are viewed as images of the ceiling beacons (known scene points), the HiBall tracker can be viewed as an implementation of the abstract image-based example initially introduced in section 1.2 on page 39 (see figures 1.4-1.6) and later used in chapter 5. Hence my frequent references to a HiBall lens and sensor pair as a camera. Welch Thesis at 192-93.</p> <p><i>See Disclosures with respect to Element 1.pre, <i>supra</i>; see also Defendants' Invalidity Contentions for further discussion.</i></p>
[1.b] a sensor subsystem coupled to the estimation subsystem and configured to provide configuration data to the estimation subsystem and to provide measurement information to the	<p>At least under Plaintiffs' apparent infringement theory, Welch Thesis discloses, either expressly or inherently, a sensor subsystem coupled to the estimation subsystem and configured to provide configuration data to the estimation subsystem and to provide measurement information to the estimation subsystem for localizing an object. In the alternative, this element would be obvious over Welch Thesis in light of the other references disclosed in Defendants' Invalidity Contentions and/or the knowledge of one of ordinary skill in the art.</p> <p><i>See, e.g.:</i></p> <p>A Kalman filter can be used to estimate a globally-observable process by sequentially incorporating only measurements of locally-unobservable processes. The use of a Kalman filter in such a manner offers several</p>

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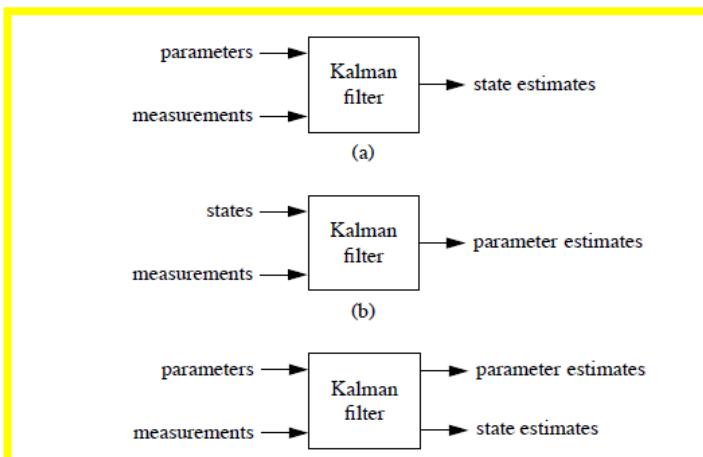
CLAIM 1	Welch Thesis
estimation subsystem for localizing an object;	<p>advantages: (1) a flexible framework for heterogeneous multisensor data fusion; (2) a unique opportunity to perform concurrent device autocalibration; and in a system that allows only sequential measurements, (3) significantly improved estimate rates and latencies; and (4) avoidance of the incorrect simultaneity assumption. Welch Thesis at 43.</p> <p>The Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) means of using noisy measurements to estimate the state of a linear system, while minimizing the expected mean-squared estimation error.</p> <p>Welch Thesis at 45.</p>  <p>Figure 2.2 consists of three sub-diagrams labeled (a), (b), and (c), each showing a 'Kalman filter' block. (a) Parameters enter the filter from the top left, and measurements enter from the bottom left. The filter outputs state estimates to the right. (b) States enter the filter from the top left, and measurements enter from the bottom left. The filter outputs parameter estimates to the right. (c) Parameters enter the filter from the top left, and measurements enter from the bottom left. The filter outputs both parameter estimates (top right) and state estimates (bottom right).</p> <p>Figure 2.2: State versus parameter estimation. (a) The system parameters are known, and are used with the measurements to estimate the states. (b) For calibration purposes, known states can be used with measurements to estimate the system parameters. (c) A set of parameters can be used in conjunction with measurements to estimate another (not necessarily disjoint) set of parameters and the states.</p> <p>Welch Thesis at 49.</p> <p>The SCAAT method represents an unusual approach to Kalman filter based multisensor data fusion. Because the filter operates on single sensor measurements, new estimates can be computed as soon as measurements from an individual sensor of any type become available, in virtually any order, and at any</p>

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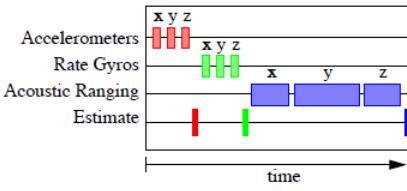
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	<p>(possibly varying) rate. Such flexibility allows measurements from any combination of devices to be interlaced in the most convenient and expeditious fashion, ensuring that each estimate is computed from the most recent data offered by any combination of devices. The information from the various observations can then be blended using either a single SCAAT KF with multiple measurement models, or separate SCAAT filters (and thus statistics) each with single measurement models, in which case the estimates from the various models can be blended using a statistical multi-model approach (see for example [Bar-Shalom93]).</p> <p>Welch Thesis at 56-57.</p> <p>For the sake of illustration, imagine an inertial-acoustical hybrid tracking system composed of three accelerometers, three rate gyros, and an acoustical line-of-sight system (to control drift from the inertial sensors). Note that not only will the acoustical measurements take longer than the inertial measurements, the acoustical measurement times will vary with distance between the source and sensors. A conventional method for data fusion might repeat the fixed pattern shown in figure 2.7. Notice that an estimate is produced only after collecting an orthogonal group of measurements from each (any one) subsystem.</p>  <p>Figure 2.7: Timing diagram for a hypothetical conventional hybrid tracking system. The state estimate is updated only after each group of 3 homogeneous measurements.</p> <p>In contrast, a SCAAT implementation might interleave sensor measurements as depicted in figure 2.8. Note the flexibility of measurement type, availability, rate, and ordering. Again because an estimate is produced with every sensor measurement, latency is reduced and the estimation rate is increased.</p>

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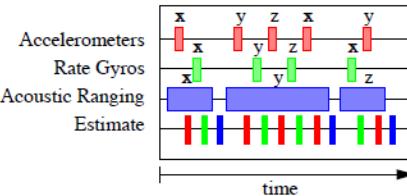
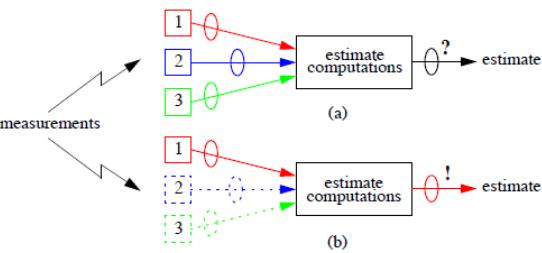
CLAIM 1	Welch Thesis
	<p data-bbox="608 246 1015 442">  </p> <p data-bbox="508 453 1121 523"> Figure 2.8: Timing diagram for a SCAAT inertial-acoustic hybrid tracking system. The state estimate is updated whenever an individual measurement becomes available. </p> <p data-bbox="502 548 804 580">Welch Thesis at 57-58.</p> <p data-bbox="502 616 1917 833"> On the other hand, because the SCAAT method generates a new tracking estimate with each individual measurement, individual device imperfections are more readily identified. Furthermore, because the simultaneity assumption is avoided, the motion restrictions discussed in section 2.3.2 are removed, and autocalibration can be performed while concurrently tracking a target under normal conditions. The specific autocalibration method is presented in chapter 4, with experimental results in chapter 6. </p> <p data-bbox="502 809 762 842">Welch Thesis at 61.</p> <p data-bbox="530 882 1072 1135">  </p> <p data-bbox="536 1147 1064 1266"> Figure 2.11: Autocalibration and attribution of measurement error. (a) Most algorithms operate on multiple measurements as a group, hence uncertainty or error (represented by the ellipses) in the final estimates is difficult to attribute to any individual sensor. (b) With the SCAAT method, uncertainty in final estimates can more easily be attributed to a particular individual sensor. </p> <p data-bbox="502 1290 762 1323">Welch Thesis at 62.</p>

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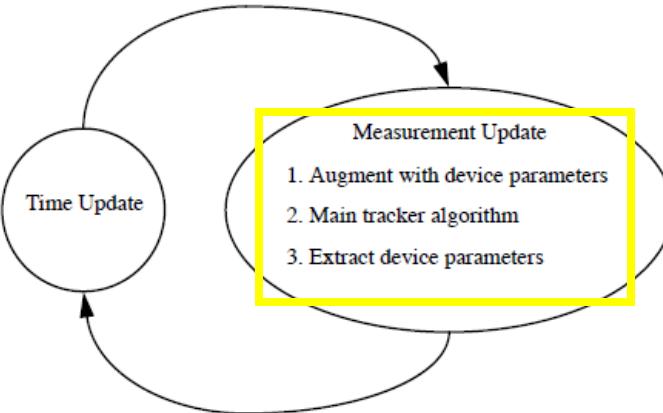
CLAIM 1	Welch Thesis
	 <p>Figure 4.12: The revised tracking algorithm for autocalibration. The time update consists of equation (4.14). The measurement update consists of equations (4.24)-(4.27), then (4.15)-(4.22), and finally equation (4.28).</p> <p><i>Welch Thesis at 102.</i></p> <p>The tracking system that I employ in my experiments is an “inside-looking-out” optoelectronic system designed for interactive computer graphics or virtual environments. The system, which we call the “HiBall tracker”, is an improved version of the wide-area system described in [Ward92]. In these systems, user-mounted optical sensors observe infrared light-emitting diodes (LEDs) or beacons mounted in the ceiling above the user. The locations of the beacons are known (to some degree) so observations of them can be used to estimate the user’s position and orientation.</p> <p><i>Welch Thesis at 191.</i></p>

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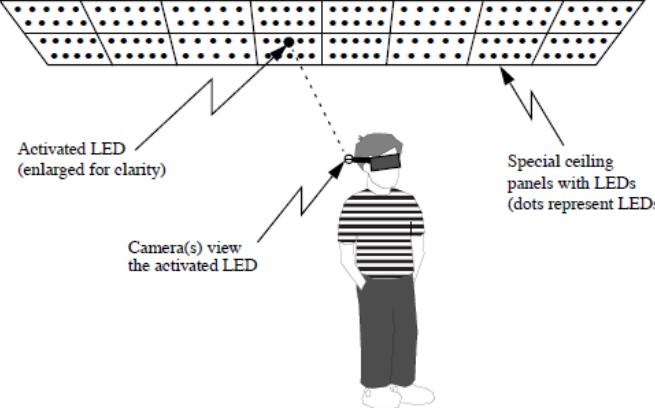
CLAIM 1	Welch Thesis
	 <p data-bbox="544 665 1199 740">Figure D.1: An outward-looking optoelectronic tracking system. User-mounted cameras look outward (generally upward) at active beacons in the environment.</p> <p data-bbox="502 757 777 789">Welch Thesis at 191.</p> <p data-bbox="502 829 1989 1046">One goal of the HiBall system is to provide a user with <i>wide-area</i> tracking. To this end, the LEDs are installed in special ceiling panels that replace standard-size acoustic ceiling tiles. (See figure D.1.) These tiles can be installed over a large area, thus providing a large working area. In fact, the current UNC installation consists of enough ceiling tiles to cover an area of approximately 5x5 meters, with a corresponding total of over 3,000 LEDs. The LED positions in world coordinates are initially estimated based on the ceiling panel design, which has them installed in a regular two-dimensional grid.</p> <p data-bbox="502 1083 1968 1230">The LEDs are connected to special circuit boards that are mounted on (above) the ceiling tiles, and these circuit boards are then connected to a computer. Thus LEDs can be individually activated under computer control as needed for the SCAAT observations. (The ceiling circuitry allows beacon activation at over 5000 LEDs per second.)</p> <p data-bbox="502 1230 777 1263">Welch Thesis at 192.</p> <p data-bbox="502 1302 1989 1405">In the original system described by [Ward92] the user wore a relatively large head-mounted mechanical fixture that supported several individually self-contained optical sensors or “cameras” and a backpack that contained the necessary signal processing and A/D conversion circuitry as shown in figure D.2.</p>

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	<p>In the new system the camera fixture and backpack in figure D.2 are together replaced by a relatively small sensor cluster called the HiBall. Figure D.3 is a picture of an unpopulated HiBall with a golf ball to convey a notion of size.</p> <p>A populated HiBall contains six lenses, six photodiodes with infrared filters, and all of the necessary circuitry for signal processing, A/D conversion, control, and high-speed serial communication. It is designed so that each photodiode can view infrared beacons (LEDs in this case) through each of several adjacent lenses, thus implementing up to 26 distinct infrared cameras.</p> <p>The photodiodes provide four signals that together indicate the position of the centroid of light (infrared in this case) as it appears on the two-dimensional photodiode surface. At any point in time, the internal A/D conversion circuitry can sample these signals for any one photodiode. These samples would then be sent to an external computer via a high-speed serial link where they would be converted to the measurement that reflect the position of the image of the infrared beacon on the two-dimensional photodiode.</p> <p>If the photodiode measurements are viewed as images of the ceiling beacons (known scene points), the HiBall tracker can be viewed as an implementation of the abstract image-based example initially introduced in section 1.2 on page 39 (see figures 1.4-1.6) and later used in chapter 5. Hence my frequent references to a HiBall lens and sensor pair as a camera. Welch Thesis at 192-93.</p> <p><i>See also</i> Welch Thesis Chapter 2.5 (describing autocalibration for sensor subsystems); Chapter 4.4 (autocalibration using SCAAT algorithm); Chapter 6.1 (describing autocalibration of HiBall sensor system using SCAAT).</p> <p><i>See</i> Disclosures with respect to Element 1.a, <i>supra</i>; <i>see also</i> Defendants' Invalidity Contentions for further discussion.</p>
[1.c] wherein the estimation subsystem is configured to update a location estimate for the object based on configuration data and	At least under Plaintiffs' apparent infringement theory, Welch Thesis discloses, either expressly or inherently, wherein the estimation subsystem is configured to update a location estimate for the object based on configuration data and measurement information accepted from the sensor subsystem. In the alternative, this element would be obvious over Welch Thesis in light of the other references disclosed in Defendants' Invalidity Contentions and/or the knowledge of one of ordinary skill in the art.

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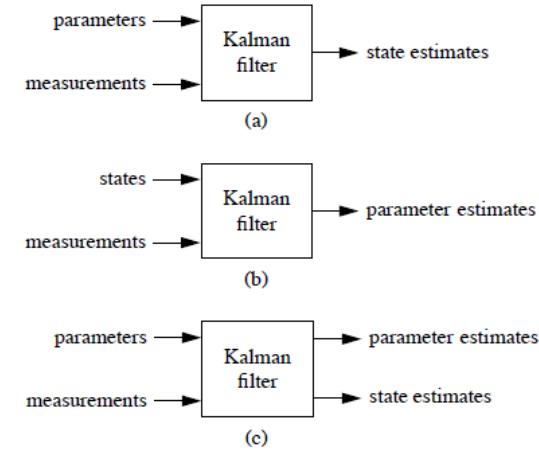
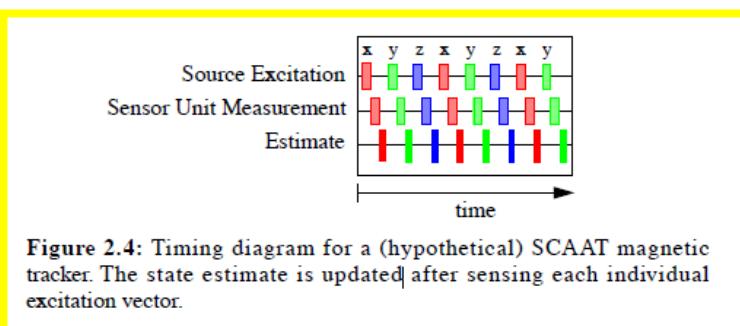
CLAIM 1	Welch Thesis
<p>measurement information accepted from the sensor subsystem.</p> <p><i>See, e.g.:</i></p>  <p>(a) Parameters → Kalman filter → State estimates Measurements → Kalman filter</p> <p>(b) States → Kalman filter → Parameter estimates Measurements → Kalman filter</p> <p>(c) Parameters → Kalman filter → Parameter estimates Measurements → Kalman filter → State estimates</p> <p>Figure 2.2: State versus parameter estimation. (a) The system parameters are known, and are used with the measurements to estimate the states. (b) For calibration purposes, known states can be used with measurements to estimate the system parameters. (c) A set of parameters can be used in conjunction with measurements to estimate another (not necessarily disjoint) set of parameters and the states.</p> <p>Welch Thesis at 49.</p>  <p>Source Excitation: x, y, z, x, y, z, x, y Sensor Unit Measurement: Red, Green, Blue, Red, Green, Blue, Red, Green Estimate: Red, Green, Blue, Red, Green, Blue, Red, Green time</p> <p>Figure 2.4: Timing diagram for a (hypothetical) SCAAT magnetic tracker. The state estimate is updated after sensing each individual excitation vector.</p> <p>Welch Thesis at 52.</p>	

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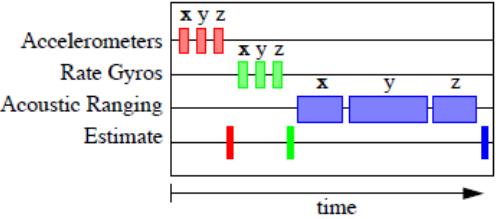
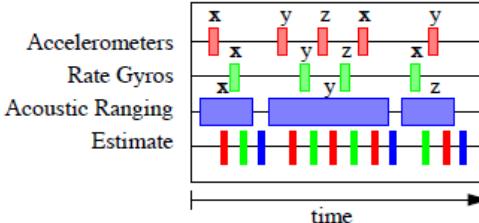
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	<p>Figure 2.7: Timing diagram for a hypothetical conventional hybrid tracking system. The state estimate is updated only after each group of 3 homogeneous measurements.</p> <p>Welch Thesis at 57.</p>  <p>Figure 2.8: Timing diagram for a SCAAT inertial-acoustic hybrid tracking system. The state estimate is updated whenever an individual measurement becomes available.</p> <p>Welch Thesis at 58.</p> 

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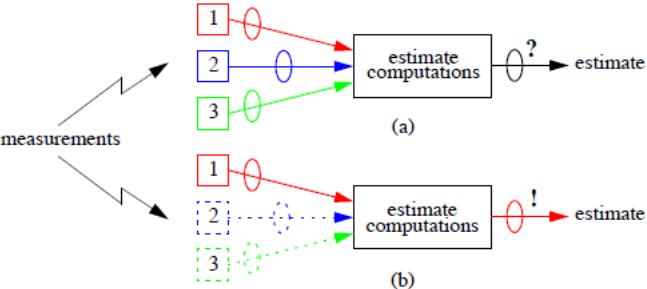
CLAIM 1	Welch Thesis
	 <p data-bbox="523 551 1170 698">Figure 2.11: Autocalibration and attribution of measurement error. (a) Most algorithms operate on multiple measurements as a group, hence uncertainty or error (represented by the ellipses) in the final estimates is difficult to attribute to any individual sensor. (b) With the SCAAT method, uncertainty in final estimates can more easily be attributed to a particular individual sensor.</p> <p data-bbox="523 711 762 740">Welch Thesis at 62.</p> <p data-bbox="523 780 1959 1155"> The Kalman filter operates in a predictor-corrector fashion, repeating a single time update and measurement update step whenever a new measurement vector becomes available. In the time update step the filter predicts what the state should be at the time of the measurements, based on the previous state estimate and a model of the process dynamics. In the measurement update step the filter uses the newly available measurement vector to correct the predicted state. In a normal implementation, depicted in figure 3.2, the time and measurement steps do not occur until all of the components of the measurement vector are available, i.e. until the state can be determined uniquely from the measurement vector. The measurement update step then processes the entire measurement vector in one batch, e.g. all three measurements in figure 3.2. This batch processing of the measurement data is relatively inflexible and can be computationally expensive if the measurement vector is large. </p> <p data-bbox="523 1155 762 1184">Welch Thesis at 65.</p> <p data-bbox="523 1220 1981 1400"> The use of a Kalman filter requires not only a dynamic model as described in section 4.2.1, but also a measurement model. The measurement model is used to predict the ideal noise-free response of each sensor and source pair, given the filter's current estimate of the target state as in equations (4.2) and (4.3). The prediction is then compared with an actual measurement, and the results are used to generate a correction for the filter's current estimate of the target state. </p> <p data-bbox="523 1400 762 1429">Welch Thesis at 78.</p>

Exhibit E-21

CLAIM 1	Welch Thesis
	<p>If one is uncertain about the 3D locations of the beacons, and/or wishes to calibrate (estimate) the positions concurrently while tracking, then guideline (b) would break these two sets into eight sets, each with one 2D camera and one beacon. Finally, per guideline (c) one would note that the eight camera-beacon pairs each yield a (u, v) image coordinate, i.e. $ms = 2$ scalar elements. If there were more source and sensor types, one would repeat this process per guideline (d).</p> <p>Welch Thesis at 80-81.</p> <p>In light of the device isolation discussion in section 2.5.4 on page 61, the application of the above guidelines in the general case leads to the following heuristic for choosing the SCAAT Kalman filter measurement elements (constraints): During each SCAAT Kalman filter measurement update one should observe a single sensor and source pair only. Thus for the two-camera, four-beacon example, we could have immediately determined that each SCAAT Kalman filter measurement update should incorporate the (u, v) image coordinate of one beacon as seen in one camera. Each such observation could in fact be considered a single geometric constraint: the intersection of a line, the line from the beacon to the principal point of the camera lens, and a plane, the image plane.</p> <p>Welch Thesis at 81.</p> <p>Figure 4.2: Geometric view of state change during time update step. Per the derivatives in the state, the target is predicted to move and reorient since the time of the last filter estimate. Note that the target rotation is maintained incrementally in the state so the state orientation is zero before the time update and non-zero afterwards. The derivative elements of the state have been omitted and the spacial relationship exaggerated for clarity.</p> <p>Welch Thesis at 85.</p>

Exhibit E-21

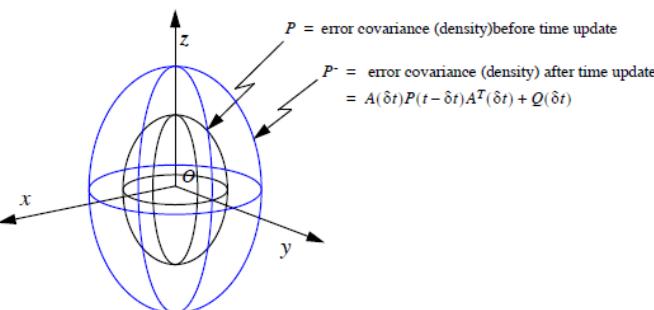
CLAIM 1	Welch Thesis
	 <p data-bbox="528 563 1140 709">Figure 4.3: Geometric view of error covariance change during time update step. The change is shown by a growing probability density for each of x, y, and z. Note that reorientation is possible in general, but not for the dynamic model given in section 4.2.1. To visualize with Euclidean dimensions, the density has been limited to 3D: x, y, and z only. The shape, magnitude, and orientation are illustrative only.</p> <p data-bbox="502 726 760 758">Welch Thesis at 85.</p>

Exhibit E-21

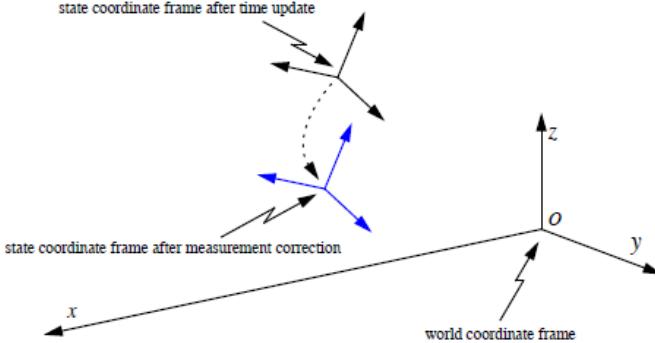
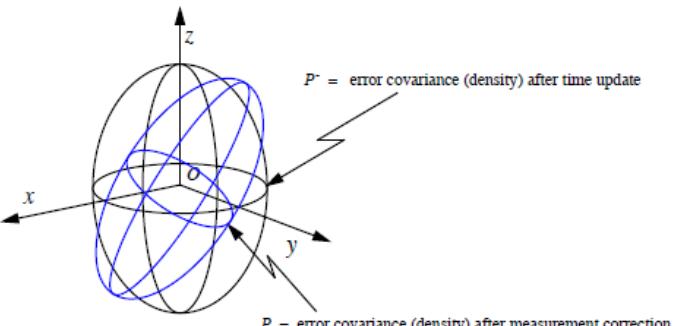
CLAIM 1	Welch Thesis
	 <p data-bbox="559 620 1172 767">Figure 4.9: Geometric view of state change after measurement correction. Per the information in the measurement residual, the <i>a posteriori</i> state estimate is formed, i.e. the estimated target coordinate frame is moved and reoriented. Compare this with figure 4.2 on page 85. (Again the derivative elements of the state have been omitted and the spacial relationship exaggerated for clarity.)</p>  <p data-bbox="559 1126 1214 1297">Figure 4.10: Geometric view of error covariance change after measurement update. The change is shown by a refined probability density for each of x, y, and z. Note that in general the density is reoriented to reflect the constraint provided by the measurement. Compare this with figure 4.3 on page 85. (Again to visualize with Euclidean dimensions, the density has been limited to 3D: x, y, and z only. The absolute shape, magnitude, and orientation are illustrative only.)</p> <p data-bbox="502 1313 756 1346">Welch Thesis at 95.</p>

Exhibit E-21

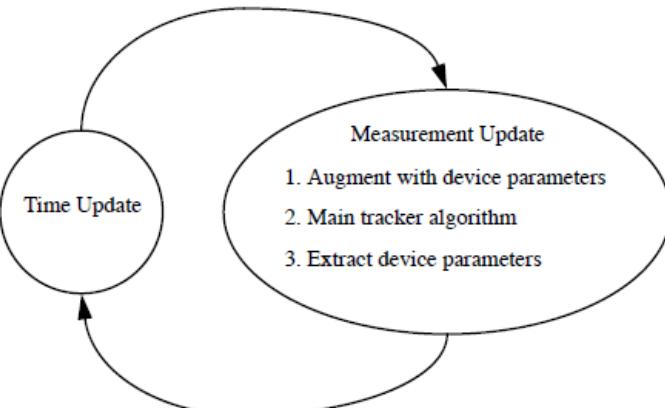
CLAIM 1	Welch Thesis
	 <p>Figure 4.12: The revised tracking algorithm for autocalibration. The time update consists of equation (4.14). The measurement update consists of equations (4.24)-(4.27), then (4.15)-(4.22), and finally equation (4.28).</p> <p><i>Welch Thesis at 102.</i></p> <p>While the total additional floating-point operations presented in table 5.2 may appear daunting, keep in mind that for a SCAAT implementation (in particular) m is likely to be relatively small, e.g. $m = 2$ for the previous image-based examples. In addition, n_π is likely to be relatively small for most devices, e.g. $n_\pi = n_b = 3$ when trying to autocalibrate (better estimate) scene point locations for the same example system.</p> <p><i>Welch Thesis at 115.</i></p> <p>The Kalman filter estimates a process by using a form of feedback control: the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. As such, the equations for the Kalman filter fall into two groups: time update equations and measurement update equations. The time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time step. The measurement update equations are responsible for the feedback—i.e. for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate. The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as corrector equations. Indeed the final estimation algorithm</p>

Exhibit E-21

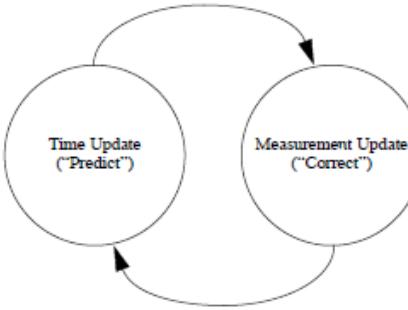
CLAIM 1	Welch Thesis
	<p>resembles that of a predictor-corrector algorithm for solving numerical problems as shown in figure B.1. Welch Thesis at 170-71.</p>  <p>Figure B.1: The ongoing discrete Kalman filter cycle. The <i>time update</i> projects the current state estimate ahead in time. The <i>measurement update</i> adjusts the projected estimate by an actual measurement at that time. Notice the resemblance to a <i>predictor-corrector</i> algorithm</p> <p>Welch Thesis at 171.</p> <p>To use Powell's method, I needed to define a cost function that returned a scalar indication of the "goodness" of a particular set of parameters. In simulations I had access to both the estimated filter state and the "true" state (see "Motion Bandwidth" below) for several motion data sets as described in section E.1. Again employing a scheme similar to that of Azuma and Bishop, I designed a special simulation framework for the purpose of parameter optimization. At every filter update step I compute the locations (in world coordinates) of three points arranged in a triangle that is oriented upright and faces the HiBall approximately one meter in front of the HiBall. I compute these three points for both the estimated filter state and the true state, and then I compute the average distance between the respective estimated and true point groups. This average distance provides a per-estimate scalar cost, which I then average for an entire simulation run (for a particular data set) to obtain the necessary scalar cost for a particular parameter set $P[N]$. This approach nicely combines position and orientation error into a single cost. The parameters found using this method for various test cases are given in section 6.2.1 of chapter 6.</p> <p>Welch Thesis at 198.</p> <p><i>See also</i> Welch Thesis Chapter 2.5 (describing autocalibration for sensor subsystems); Chapter 3.2 (describing sequential estimate updates performed by the SCAAT algorithm as new measurement data is collected by the</p>

Exhibit E-21

CLAIM 1	Welch Thesis
	<p>system); Chapter 4.3 (use of the SCAAT algorithm for tracking to predict and correct sensor measurements); Chapter 4.4 (autocalibration using SCAAT algorithm); Chapter 6.1 (describing autocalibration of HiBall sensor system using SCAAT).</p> <p><i>See</i> Disclosures with respect to Element 1.b, <i>supra</i>; <i>see also</i> Defendants' Invalidity Contentions for further discussion.</p>

B. DEPENDENT CLAIM 2

CLAIM 2	Welch Thesis
<p>[2] The system of claim 1 wherein the sensor subsystem includes one or more sensor modules, each providing an interface for interacting with a corresponding set of one or more sensing elements.</p>	<p>At least under Plaintiffs' apparent infringement theory, Welch Thesis discloses, either expressly or inherently, the system of claim 1 wherein the sensor subsystem includes one or more sensor modules, each providing an interface for interacting with a corresponding set of one or more sensing elements. In the alternative, this element would be obvious over Welch Thesis in light of the other references disclosed in Defendants' Invalidity Contentions and/or the knowledge of one of ordinary skill in the art.</p> <p><i>See, e.g.:</i></p> <p>A Kalman filter can be used to estimate a globally-observable process by sequentially incorporating only measurements of locally-unobservable processes. The use of a Kalman filter in such a manner offers several advantages: (1) a flexible framework for heterogeneous multisensor data fusion; (2) a unique opportunity to perform concurrent device autocalibration; and in a system that allows only sequential measurements, (3) significantly improved estimate rates and latencies; and (4) avoidance of the incorrect simultaneity assumption.</p> <p>Welch Thesis at 43.</p> <p>The Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) means of using noisy measurements to estimate the state of a linear system, while minimizing the expected mean-squared estimation error.</p> <p>Welch Thesis at 45.</p>

Exhibit E-21

CLAIM 2	Welch Thesis
	<p>2.1.2 Data Fusion</p> <p>The Kalman filter assumes that the system being estimated has a <i>measurement equation</i> of the form given in equation (2.1) where the matrix $H(t_k)$ relates the state vector $\hat{x}(t_k)$ to the measurement vector $\hat{z}(t_k)$, and the vector $\hat{v}(t_k)$ represents the measurement noise. Further details are presented in chapter 4 and can be found in Kalman filter texts such as [Brown92, Gelb74, Jacobs93, Lewis86].</p> $\hat{z}(t_k) = H(t_k)\hat{x}(t_k) + \hat{v}(t_k) \quad (2.1)$ <p>If the system being estimated has multiple forms of observation, there would be multiple corresponding measurement equations equation (2.1), i.e. multiple instances of the matrix $H(t_k)$, each representing a different relationship. By using the appropriate $H(t_k)$ for each type of measurement, the filter effectively combines, blends, or <i>fuses</i> the information contained in the heterogeneous measurements.</p> <p>This capability for heterogeneous <i>data fusion</i>, combined with the properties discussed in section 2.1.1, has made the Kalman filter a very popular means of data fusion. For example the Kalman filter has been used for navigation [Geier87, Mahmoud94, Watanabe94], for virtual environment tracking [Azuma95, Emura94, Foxlin96], and for 3D scene modeling [Grandjean89, VanPabst95].</p> <p><i>Welch Thesis at 46.</i></p>

Exhibit E-21

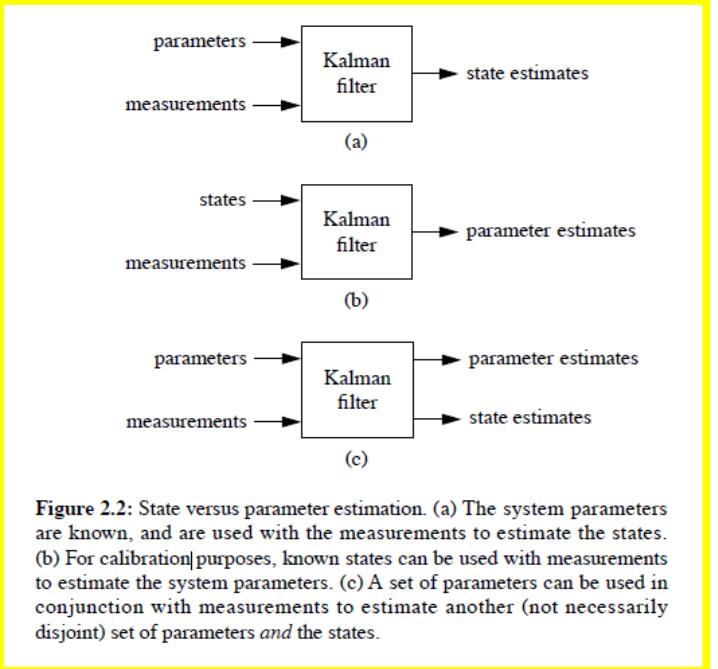
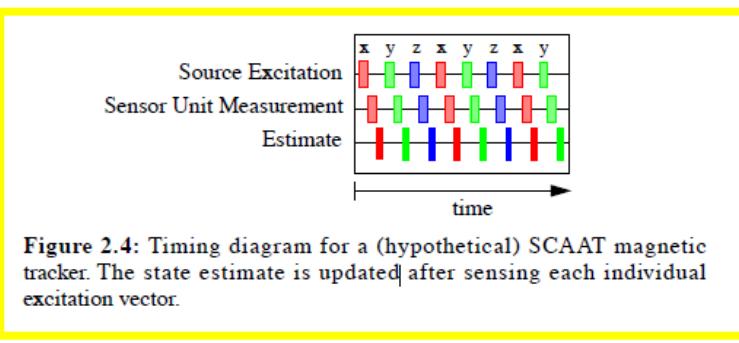
CLAIM 2	Welch Thesis
	 <p>Figure 2.2: State versus parameter estimation. (a) The system parameters are known, and are used with the measurements to estimate the states. (b) For calibration purposes, known states can be used with measurements to estimate the system parameters. (c) A set of parameters can be used in conjunction with measurements to estimate another (not necessarily disjoint) set of parameters and the states.</p>
	<p>Welch Thesis at 49.</p>  <p>Figure 2.4: Timing diagram for a (hypothetical) SCAAT magnetic tracker. The state estimate is updated after sensing each individual excitation vector.</p> <p>The SCAAT method represents an unusual approach to Kalman filter based multisensor data fusion. Because the filter operates on single sensor measurements, new estimates can be computed as soon as</p>

Exhibit E-21

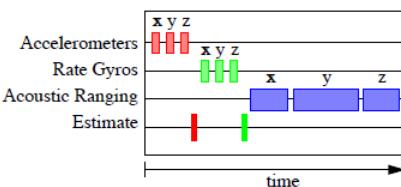
CLAIM 2	Welch Thesis
	<p>measurements from an individual sensor of any type become available, in virtually any order, and at any (possibly varying) rate. Such flexibility allows measurements from any combination of devices to be interlaced in the most convenient and expeditious fashion, ensuring that each estimate is computed from the most recent data offered by any combination of devices. The information from the various observations can then be blended using either a single SCAAT KF with multiple measurement models, or separate SCAAT filters (and thus statistics) each with single measurement models, in which case the estimates from the various models can be blended using a statistical multi-model approach (see for example [Bar-Shalom93]).</p> <p>Welch Thesis at 56-57.</p> <p>For the sake of illustration, imagine an inertial-acoustical hybrid tracking system composed of three accelerometers, three rate gyros, and an acoustical line-of-sight system (to control drift from the inertial sensors). Note that not only will the acoustical measurements take longer than the inertial measurements, the acoustical measurement times will vary with distance between the source and sensors. A conventional method for data fusion might repeat the fixed pattern shown in figure 2.7. Notice that an estimate is produced only after collecting an orthogonal group of measurements from each (any one) subsystem.</p>  <p>Figure 2.7: Timing diagram for a hypothetical conventional hybrid tracking system. The state estimate is updated only after each group of 3 homogeneous measurements.</p> <p>In contrast, a SCAAT implementation might interleave sensor measurements as depicted in figure 2.8. Note the flexibility of measurement type, availability, rate, and ordering. Again because an estimate is produced with every sensor measurement, latency is reduced and the estimation rate is increased.</p>

Exhibit E-21

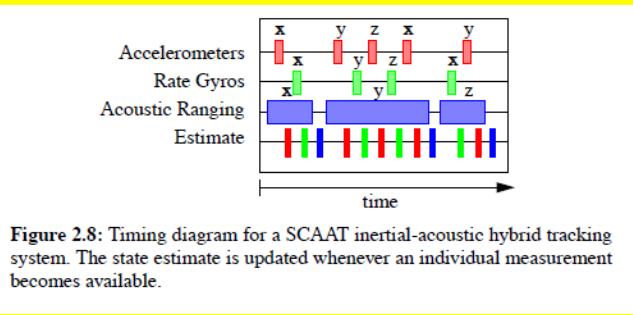
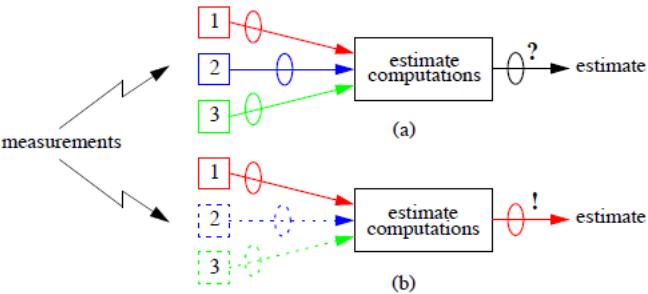
CLAIM 2	Welch Thesis
	<p data-bbox="530 241 1163 556">  Figure 2.8: Timing diagram for a SCAAT inertial-acoustic hybrid tracking system. The state estimate is updated whenever an individual measurement becomes available. </p> <p data-bbox="515 567 819 600">Welch Thesis at 57-58.</p> <p data-bbox="515 633 1930 817"> On the other hand, because the SCAAT method generates a new tracking estimate with each individual measurement, individual device imperfections are more readily identified. Furthermore, because the simultaneity assumption is avoided, the motion restrictions discussed in section 2.3.2 are removed, and autocalibration can be performed while concurrently tracking a target under normal conditions. The specific autocalibration method is presented in chapter 4, with experimental results in chapter 6. </p> <p data-bbox="515 817 777 850">Welch Thesis at 61.</p> <p data-bbox="536 894 1184 1188">  Figure 2.11: Autocalibration and attribution of measurement error. (a) Most algorithms operate on multiple measurements as a group, hence uncertainty or error (represented by the ellipses) in the final estimates is difficult to attribute to any individual sensor. (b) With the SCAAT method, uncertainty in final estimates can more easily be attributed to a particular individual sensor. </p> <p data-bbox="515 1356 777 1388">Welch Thesis at 62.</p>

Exhibit E-21

CLAIM 2	Welch Thesis
	<p>The Kalman filter operates in a predictor-corrector fashion, repeating a single time update and measurement update step whenever a new measurement vector becomes available. In the time update step the filter predicts what the state should be at the time of the measurements, based on the previous state estimate and a model of the process dynamics. In the measurement update step the filter uses the newly available measurement vector to correct the predicted state. In a normal implementation, depicted in figure 3.2, the time and measurement steps do not occur until all of the components of the measurement vector are available, i.e. until the state can be determined uniquely from the measurement vector. The measurement update step then processes the entire measurement vector in one batch, e.g. all three measurements in figure 3.2. This batch processing of the measurement data is relatively inflexible and can be computationally expensive if the measurement vector is large.</p> <p>Welch Thesis at 65.</p> <p>The use of a Kalman filter requires not only a dynamic model as described in section 4.2.1, but also a measurement model. The measurement model is used to predict the ideal noise-free response of each sensor and source pair, given the filter's current estimate of the target state as in equations (4.2) and (4.3). The prediction is then compared with an actual measurement, and the results are used to generate a correction for the filter' current estimate of the target state.</p> <p>Welch Thesis at 78.</p> <p>In light of the device isolation discussion in section 2.5.4 on page 61, the application of the above guidelines in the general case leads to the following heuristic for choosing the SCAAT Kalman filter measurement elements (constraints): During each SCAAT Kalman filter measurement update one should observe a single sensor and source pair only. Thus for the two-camera, four-beacon example, we could have immediately determined that each SCAAT Kalman filter measurement update should incorporate the (u,v) image coordinate of one beacon as seen in one camera. Each such observation could in fact be considered a single geometric constraint: the intersection of a line, the line from the beacon to the principal point of the camera lens, and a plane, the image plane.</p> <p>Welch Thesis at 81.</p>

Exhibit E-21

CLAIM 2	Welch Thesis
	<p>Figure 4.2: Geometric view of state change during time update step. Per the derivatives in the state, the target is predicted to move and reorient since the time of the last filter estimate. Note that the target rotation is maintained incrementally in the state so the state orientation is zero before the time update and non-zero afterwards. The derivative elements of the state have been omitted and the spacial relationship exaggerated for clarity.</p> <p>Welch Thesis at 85.</p> <p>P = error covariance (density) before time update</p> <p>P' = error covariance (density) after time update $= A(\delta t)P(t - \delta t)A^T(\delta t) + Q(\delta t)$</p> <p>Figure 4.3: Geometric view of error covariance change during time update step. The change is shown by a growing probability density for each of x, y, and z. Note that reorientation is possible in general, but not for the dynamic model given in section 4.2.1. To visualize with Euclidean dimensions, the density has been limited to 3D: x, y, and z only. The shape, magnitude, and orientation are illustrative only.</p> <p>Welch Thesis at 85.</p>

Exhibit E-21

CLAIM 2	Welch Thesis
	<p>Continuing with the image-based measurement example, the situation is depicted in figure 4.8. The filter has some notion of where the target is located and how it is oriented, which determines its prediction of the measurement \vec{z}_p (the image coordinates of the known scene point). But the actual measurement $\vec{z}_o(t)$ indicates what the camera really “saw”. The difference between the two is the residual—the error in the measurement prediction.</p> <p>Welch Thesis at 92.</p>

Exhibit E-21

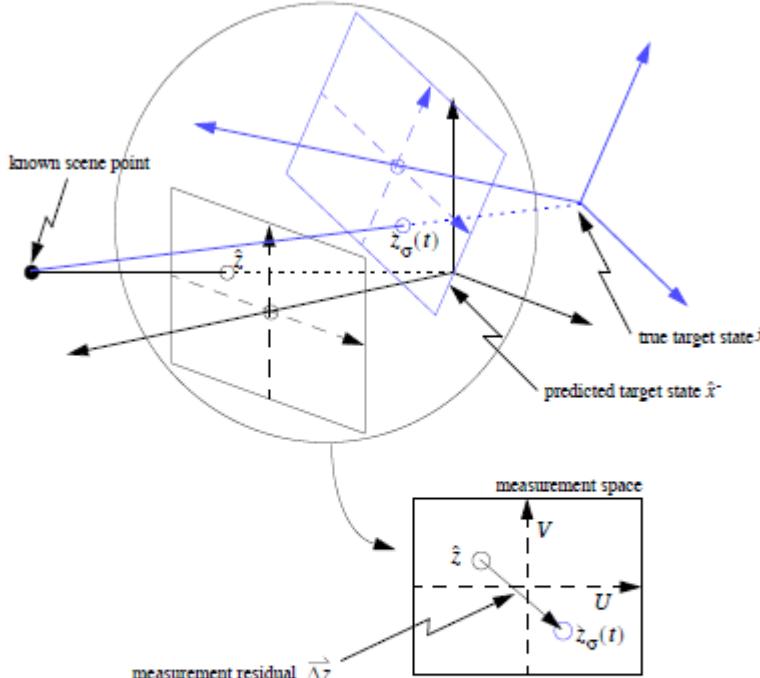
CLAIM 2	Welch Thesis
	 <p>The diagram illustrates the measurement residual in a 3D scene and its projection into a 2D measurement space. In the top part, a 3D coordinate system shows a 'known scene point' (black dot) and a 'true target state \hat{x}' (blue dot). A 'predicted target state \hat{x}^*' (red dot) is shown, along with a 'measurement residual $\hat{z} - \hat{z}_\sigma(t)$' (blue vector). In the bottom part, a 2D 'measurement space' is shown with axes U and V. The predicted measurement \hat{z} is at the origin, and the actual measurement $\hat{z}_\sigma(t)$ is shown as a blue vector.</p> <p>Figure 4.8: The measurement residual. Continuing with the image-based measurement example, the residual is the m_σ-dimensional vector from the predicted measurement (image-plane coordinates) \hat{z} to the actual measurement $\hat{z}_\sigma(t)$. The measurement prediction is what the filter thinks it will see given the predicted state, the actual measurement comes directly from the camera. (The relationship between the true and predicted state has been exaggerated for the purpose of illustration.)</p> <p><i>Welch Thesis at 93.</i></p>

Exhibit E-21

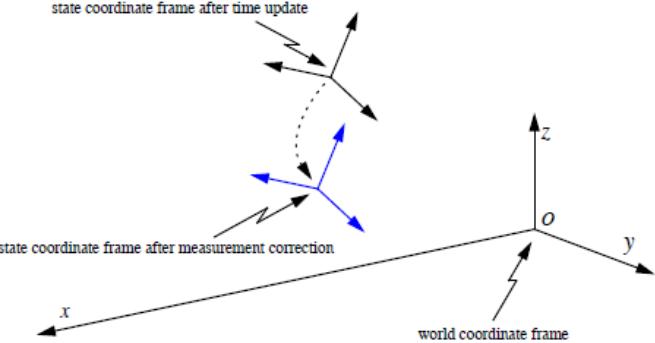
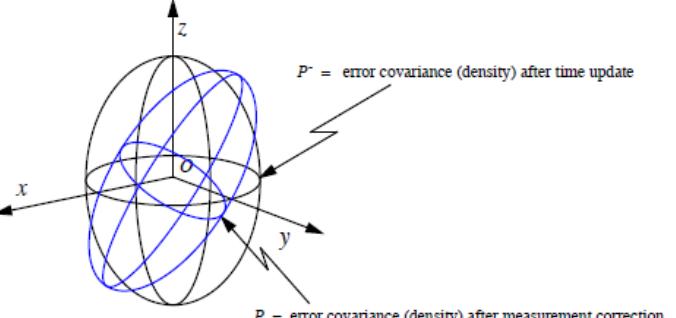
CLAIM 2	Welch Thesis
	 <p data-bbox="580 628 1193 775">Figure 4.9: Geometric view of state change after measurement correction. Per the information in the measurement residual, the <i>a posteriori</i> state estimate is formed, i.e. the estimated target coordinate frame is moved and reoriented. Compare this with figure 4.2 on page 85. (Again the derivative elements of the state have been omitted and the spacial relationship exaggerated for clarity.)</p>  <p data-bbox="580 1134 1235 1305">Figure 4.10: Geometric view of error covariance change after measurement update. The change is shown by a refined probability density for each of x, y, and z. Note that in general the density is reoriented to reflect the constraint provided by the measurement. Compare this with figure 4.3 on page 85. (Again to visualize with Euclidean dimensions, the density has been limited to 3D: x, y, and z only. The absolute shape, magnitude, and orientation are illustrative only.)</p> <p data-bbox="517 1313 770 1346">Welch Thesis at 95.</p>

Exhibit E-21

CLAIM 2	Welch Thesis
	<p>Figure 4.11: Complete sequence of filter state coordinate frame transitions. This figure repeats the depictions in figures 4.2 and 4.9, and adds the final handling of the incremental rotations. After the measurement update, the incremental rotation is factored into the external orientation, and the incremental elements are zeroed in preparation for the next filter</p> <p>Welch Thesis at 97.</p>

Exhibit E-21

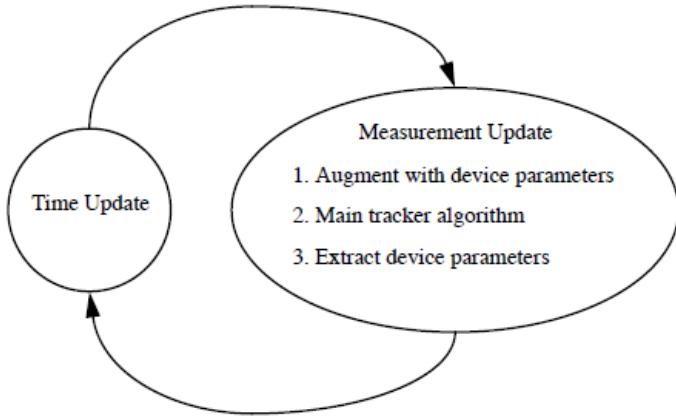
CLAIM 2	Welch Thesis
	 <p>Figure 4.12: The revised tracking algorithm for autocalibration. The time update consists of equation (4.14). The measurement update consists of equations (4.24)-(4.27), then (4.15)-(4.22), and finally equation (4.28).</p> <p><i>Welch Thesis at 102.</i></p> <p>In this chapter I describe experiments using the SCAAT approach to tracking with the UNC HiBall tracking system. See appendix D for a description of the HiBall tracking system. As part of the development of the HiBall system software, we have built an extensive simulation environment that makes use of detailed mechanical and electrical models that are based on real components. In addition, we have executed the SCAAT computations on the actual target platform to confirm the execution times, etc. See appendix E for a description of the simulation environment. We (Bishop, Chi, Fuchs, Welch et al. at UNC) hope to demonstrate a working HiBall shortly after the publication of this dissertation.</p> <p><i>Welch Thesis at 119.</i></p> <p>For the initial implementation of our HiBall system, and thus these simulations, we have decided to implement autocalibration only for the sources, the beacon positions, and not the sensors, the HiBall cameras. Thus the SCAAT implementation is configured to employ both a main HiBall filter as described below in section 6.1.1, and many individual beacon filters—one filter per LED—as described below in section 6.1.2.</p> <p><i>Welch Thesis at 119.</i></p> <p>Following the autocalibration method of section 4.4, we maintain a distinct Kalman filter for each individual beacon (LED). Because as described earlier we are primarily concerned with the position of each</p>

Exhibit E-21

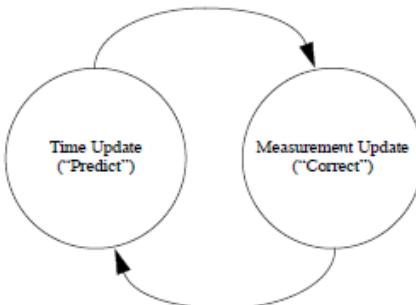
CLAIM 2	Welch Thesis
	<p>beacon in world coordinates, this is the per-beacon parameter we have chosen to autocalibrate. Welch Thesis at 120.</p> <p>The Kalman filter estimates a process by using a form of feedback control: the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. As such, the equations for the Kalman filter fall into two groups: time update equations and measurement update equations. The time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time step. The measurement update equations are responsible for the feedback—i.e. for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate. The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as corrector equations. Indeed the final estimation algorithm resembles that of a predictor-corrector algorithm for solving numerical problems as shown in figure B.1. Welch Thesis at 170-71.</p>  <p>Figure B.1: The ongoing discrete Kalman filter cycle. The <i>time update</i> projects the current state estimate ahead in time. The <i>measurement update</i> adjusts the projected estimate by an actual measurement at that time. Notice the resemblance to a <i>predictor-corrector</i> algorithm Welch Thesis at 171.</p> <p>The tracking system that I employ in my experiments is an “inside-looking-out” optoelectronic system designed for interactive computer graphics or virtual environments. The system, which we call the “HiBall tracker”, is an improved version of the wide-area system described in [Ward92]. In these systems, user-mounted optical sensors observe infrared light-emitting diodes (LEDs) or beacons mounted in the ceiling</p>

Exhibit E-21

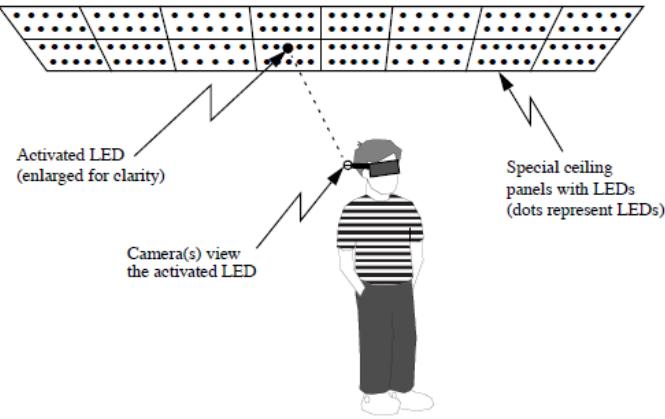
CLAIM 2	Welch Thesis
	<p>above the user. The locations of the beacons are known (to some degree) so observations of them can be used to estimate the user's position and orientation.</p> <p>Welch Thesis at 191.</p>  <p>Figure D.1: An outward-looking optoelectronic tracking system. User-mounted cameras look outward (generally upward) at active beacons in the environment.</p> <p>Welch Thesis at 191.</p> <p>One goal of the HiBall system is to provide a user with <i>wide-area</i> tracking. To this end, the LEDs are installed in special ceiling panels that replace standard-size acoustic ceiling tiles. (See figure D.1.) These tiles can be installed over a large area, thus providing a large working area. In fact, the current UNC installation consists of enough ceiling tiles to cover an area of approximately 5x5 meters, with a corresponding total of over 3,000 LEDs. The LED positions in world coordinates are initially estimated based on the ceiling panel design, which has them installed in a regular two-dimensional grid.</p> <p>The LEDs are connected to special circuit boards that are mounted on (above) the ceiling tiles, and these circuit boards are then connected to a computer. Thus LEDs can be individually activated under computer control as needed for the SCAAT observations. (The ceiling circuitry allows beacon activation at over 5000 LEDs per second.)</p> <p>Welch Thesis at 192.</p>

Exhibit E-21

CLAIM 2	Welch Thesis
	<p>In the original system described by [Ward92] the user wore a relatively large head-mounted mechanical fixture that supported several individually self-contained optical sensors or “cameras” and a backpack that contained the necessary signal processing and A/D conversion circuitry as shown in figure D.2.</p> <p>In the new system the camera fixture and backpack in figure D.2 are together replaced by a relatively small sensor cluster called the HiBall. Figure D.3 is a picture of an unpopulated HiBall with a golf ball to convey a notion of size.</p> <p>A populated HiBall contains six lenses, six photodiodes with infrared filters, and all of the necessary circuitry for signal processing, A/D conversion, control, and high-speed serial communication. It is designed so that each photodiode can view infrared beacons (LEDs in this case) through each of several adjacent lenses, thus implementing up to 26 distinct infrared cameras.</p> <p>The photodiodes provide four signals that together indicate the position of the centroid of light (infrared in this case) as it appears on the two-dimensional photodiode surface. At any point in time, the internal A/D conversion circuitry can sample these signals for any one photodiode. These samples would then be sent to an external computer via a high-speed serial link where they would be converted to the measurement that reflect the position of the image of the infrared beacon on the two-dimensional photodiode.</p> <p>If the photodiode measurements are viewed as images of the ceiling beacons (known scene points), the HiBall tracker can be viewed as an implementation of the abstract image-based example initially introduced in section 1.2 on page 39 (see figures 1.4-1.6) and later used in chapter 5. Hence my frequent references to a HiBall lens and sensor pair as a camera.</p> <p>Welch Thesis at 192-93.</p> <p><i>See also</i> Welch Thesis Chapter 2.5 (describing autocalibration for sensor subsystems); Chapter 3.2 (describing sequential estimate updates performed by the SCAAT algorithm as new measurement data is collected by the system); Chapter 4.3 (use of the SCAAT algorithm for tracking to predict and correct sensor measurements); Chapter 4.4 (autocalibration using SCAAT algorithm); Chapter 6.1 (describing autocalibration of HiBall sensor system using SCAAT).</p> <p><i>See Disclosures with respect to Claim 1, <i>supra</i>; see also Defendants’ Invalidity Contentions for further discussion.</i></p>

Exhibit E-21

C. DEPENDENT CLAIM 3

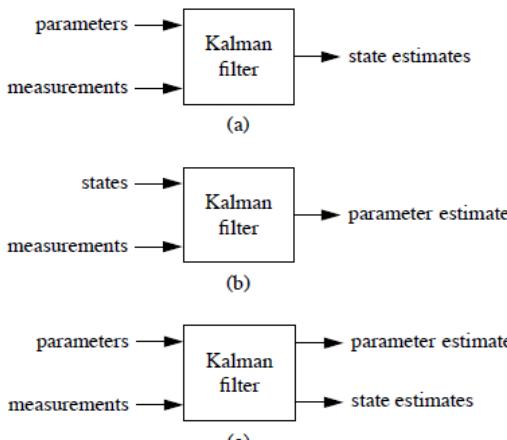
CLAIM 3	Welch Thesis
<p>[3] The system of claim 2 wherein the interface enables the sensor module to perform computations independently of an implementation of the estimation subsystem.</p>	<p>At least under Plaintiffs' apparent infringement theory, Welch Thesis discloses, either expressly or inherently, the system of claim 2 wherein the interface enables the sensor module to perform computations independently of an implementation of the estimation subsystem. In the alternative, this element would be obvious over Welch Thesis in light of the other references disclosed in Defendants' Invalidity Contentions and/or the knowledge of one of ordinary skill in the art.</p> <p><i>See, e.g.:</i></p>  <p>Figure 2.2: State versus parameter estimation. (a) The system parameters are known, and are used with the measurements to estimate the states. (b) For calibration purposes, known states can be used with measurements to estimate the system parameters. (c) A set of parameters can be used in conjunction with measurements to estimate another (not necessarily disjoint) set of parameters <i>and</i> the states.</p> <p>Welch Thesis at 49.</p>

Exhibit E-21

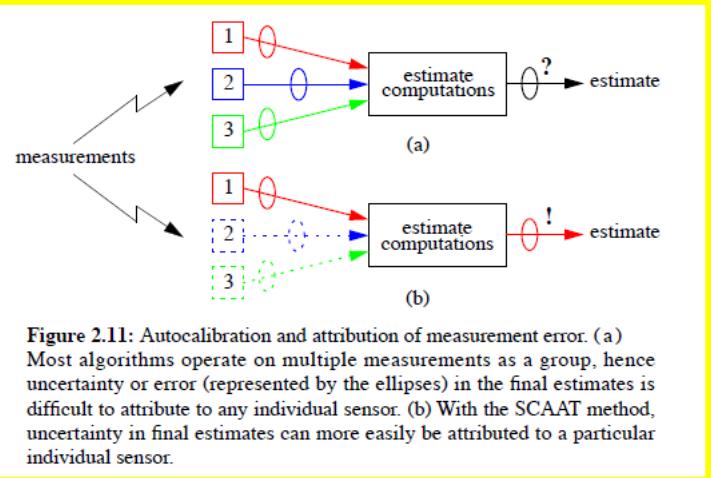
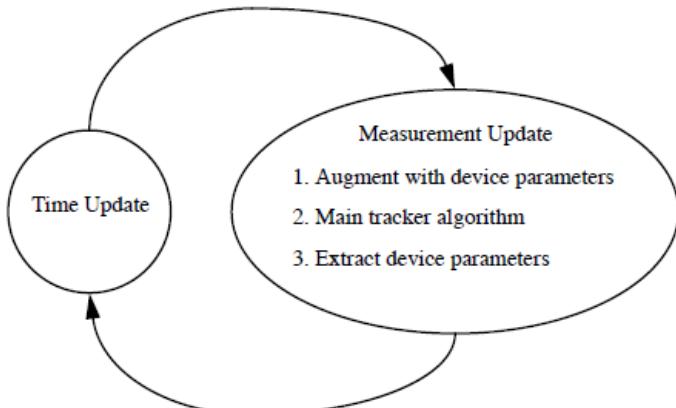
CLAIM 3	Welch Thesis
	 <p>Figure 2.11: Autocalibration and attribution of measurement error. (a) Most algorithms operate on multiple measurements as a group, hence uncertainty or error (represented by the ellipses) in the final estimates is difficult to attribute to any individual sensor. (b) With the SCAAT method, uncertainty in final estimates can more easily be attributed to a particular individual sensor.</p> <p>Welch Thesis at 62.</p>  <p>Figure 4.12: The revised tracking algorithm for autocalibration. The time update consists of equation (4.14). The measurement update consists of equations (4.24)-(4.27), then (4.15)-(4.22), and finally equation (4.28).</p> <p>Welch Thesis at 102.</p>

Exhibit E-21

CLAIM 3	Welch Thesis
	<p>In this chapter I describe experiments using the SCAAT approach to tracking with the UNC HiBall tracking system. See appendix D for a description of the HiBall tracking system. As part of the development of the HiBall system software, we have built an extensive simulation environment that makes use of detailed mechanical and electrical models that are based on real components. In addition, we have executed the SCAAT computations on the actual target platform to confirm the execution times, etc. See appendix E for a description of the simulation environment. We (Bishop, Chi, Fuchs, Welch et al. at UNC) hope to demonstrate a working HiBall shortly after the publication of this dissertation.</p> <p>Welch Thesis at 119.</p> <p>For the initial implementation of our HiBall system, and thus these simulations, we have decided to implement autocalibration only for the sources, the beacon positions, and not the sensors, the HiBall cameras. Thus the SCAAT implementation is configured to employ both a main HiBall filter as described below in section 6.1.1, and many individual beacon filters—one filter per LED—as described below in section 6.1.2.</p> <p>Welch Thesis at 119.</p> <p>Following the autocalibration method of section 4.4, we maintain a distinct Kalman filter for each individual beacon (LED). Because as described earlier we are primarily concerned with the position of each beacon in world coordinates, this is the per-beacon parameter we have chosen to autocalibrate.</p> <p>Welch Thesis at 120.</p> <p><i>See also</i> Welch Thesis Chapter 2.5 (describing autocalibration for sensor subsystems); Chapter 3.2 (describing sequential estimate updates performed by the SCAAT algorithm as new measurement data is collected by the system); Chapter 4.3 (use of the SCAAT algorithm for tracking to predict and correct sensor measurements); Chapter 4.4 (autocalibration using SCAAT algorithm); Chapter 6.1 (describing autocalibration of HiBall sensor system using SCAAT).</p> <p><i>See Disclosures with respect to Claim 2, <i>supra</i>; see also Defendants' Invalidity Contentions for further discussion.</i></p>

Exhibit E-21

D. DEPENDENT CLAIM 4

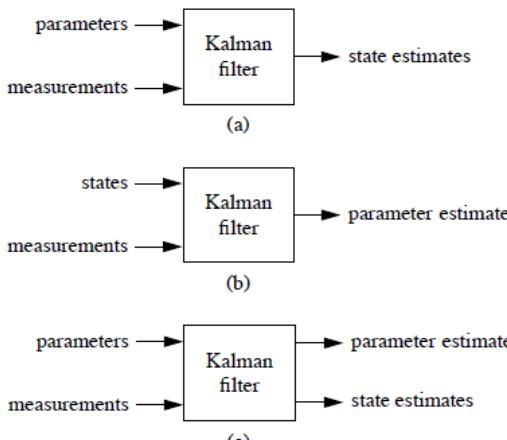
CLAIM 4	Welch Thesis
<p>[4] The system of claim 2 wherein the interface enables the estimation subsystem to perform computations independently of an implementation of the sensor modules.</p>	<p>At least under Plaintiffs' apparent infringement theory, Welch Thesis discloses, either expressly or inherently, the system of claim 2 wherein the interface enables the estimation subsystem to perform computations independently of an implementation of the sensor modules. In the alternative, this element would be obvious over Welch Thesis in light of the other references disclosed in Defendants' Invalidity Contentions and/or the knowledge of one of ordinary skill in the art.</p> <p><i>See, e.g.:</i></p>  <p>(a) parameters → Kalman filter → state estimates measurements →</p> <p>(b) states → Kalman filter → parameter estimates measurements →</p> <p>(c) parameters → Kalman filter → parameter estimates measurements → Kalman filter → state estimates</p> <p>Figure 2.2: State versus parameter estimation. (a) The system parameters are known, and are used with the measurements to estimate the states. (b) For calibration purposes, known states can be used with measurements to estimate the system parameters. (c) A set of parameters can be used in conjunction with measurements to estimate another (not necessarily disjoint) set of parameters <i>and</i> the states.</p> <p>Welch Thesis at 49.</p>

Exhibit E-21

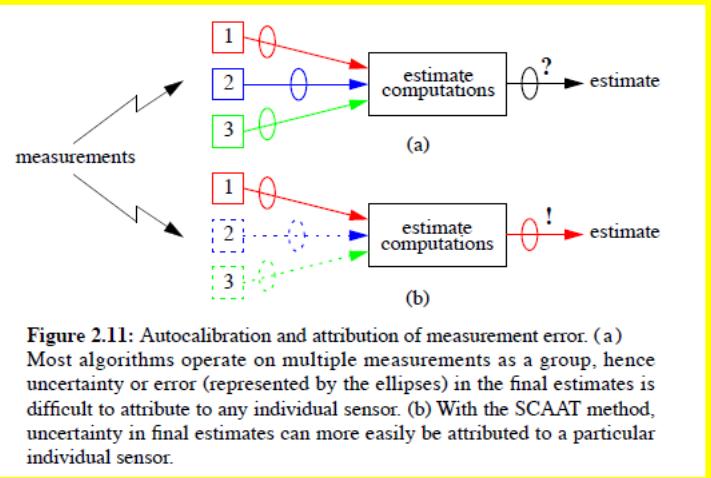
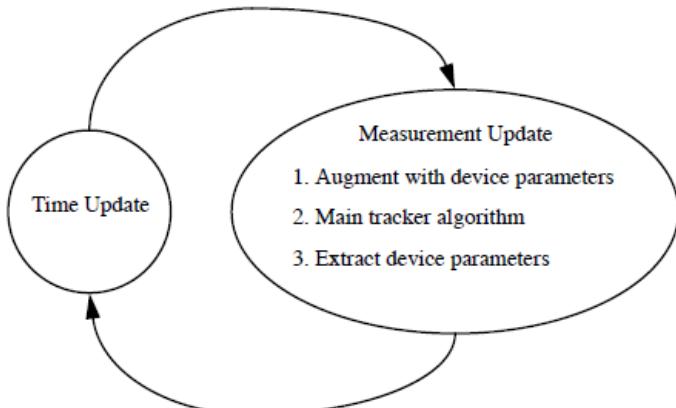
CLAIM 4	Welch Thesis
	 <p>Figure 2.11: Autocalibration and attribution of measurement error. (a) Most algorithms operate on multiple measurements as a group, hence uncertainty or error (represented by the ellipses) in the final estimates is difficult to attribute to any individual sensor. (b) With the SCAAT method, uncertainty in final estimates can more easily be attributed to a particular individual sensor.</p> <p>Welch Thesis at 62.</p>  <p>Figure 4.12: The revised tracking algorithm for autocalibration. The time update consists of equation (4.14). The measurement update consists of equations (4.24)-(4.27), then (4.15)-(4.22), and finally equation (4.28).</p> <p>Welch Thesis at 102.</p>

Exhibit E-21

CLAIM 4	Welch Thesis
	<p>In this chapter I describe experiments using the SCAAT approach to tracking with the UNC HiBall tracking system. See appendix D for a description of the HiBall tracking system. As part of the development of the HiBall system software, we have built an extensive simulation environment that makes use of detailed mechanical and electrical models that are based on real components. In addition, we have executed the SCAAT computations on the actual target platform to confirm the execution times, etc. See appendix E for a description of the simulation environment. We (Bishop, Chi, Fuchs, Welch et al. at UNC) hope to demonstrate a working HiBall shortly after the publication of this dissertation.</p> <p>Welch Thesis at 119.</p> <p>For the initial implementation of our HiBall system, and thus these simulations, we have decided to implement autocalibration only for the sources, the beacon positions, and not the sensors, the HiBall cameras. Thus the SCAAT implementation is configured to employ both a main HiBall filter as described below in section 6.1.1, and many individual beacon filters—one filter per LED—as described below in section 6.1.2.</p> <p>Welch Thesis at 119.</p> <p>Following the autocalibration method of section 4.4, we maintain a distinct Kalman filter for each individual beacon (LED). Because as described earlier we are primarily concerned with the position of each beacon in world coordinates, this is the per-beacon parameter we have chosen to autocalibrate.</p> <p>Welch Thesis at 120.</p> <p><i>See also</i> Welch Thesis Chapter 2.5 (describing autocalibration for sensor subsystems); Chapter 3.2 (describing sequential estimate updates performed by the SCAAT algorithm as new measurement data is collected by the system); Chapter 4.3 (use of the SCAAT algorithm for tracking to predict and correct sensor measurements); Chapter 4.4 (autocalibration using SCAAT algorithm); Chapter 6.1 (describing autocalibration of HiBall sensor system using SCAAT).</p> <p><i>See Disclosures with respect to Claim 2, <i>supra</i>; see also Defendants' Invalidity Contentions for further discussion.</i></p>

Exhibit E-21

E. INDEPENDENT CLAIM 6

CLAIM 6	Welch Thesis
<p>[6.pre] A method comprising:</p> <p>No party has yet asserted that the preamble is limiting, nor has the Court construed the preamble as limiting. However, to the extent that the preamble is limiting, it is disclosed by Welch Thesis.</p> <p>In the alternative, this element would be obvious over Welch Thesis in light of the other references disclosed in Defendants' Invalidity Contentions and/or the knowledge of one of ordinary skill in the art.</p> <p><i>See, e.g.:</i></p> <p>A Kalman filter can be used to estimate a globally-observable process by sequentially incorporating only measurements of locally-unobservable processes. The use of a Kalman filter in such a manner offers several advantages: (1) a flexible framework for heterogeneous multisensor data fusion; (2) a unique opportunity to perform concurrent device autocalibration; and in a system that allows only sequential measurements, (3) significantly improved estimate rates and latencies; and (4) avoidance of the incorrect simultaneity assumption. Welch Thesis at 43.</p> <p>The Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) means of using noisy measurements to estimate the state of a linear system, while minimizing the expected mean-squared estimation error.</p> <p>Welch Thesis at 45.</p> <p>The SCAAT method represents an unusual approach to Kalman filter based multisensor data fusion. Because the filter operates on single sensor measurements, new estimates can be computed as soon as measurements from an individual sensor of any type become available, in virtually any order, and at any (possibly varying) rate. Such flexibility allows measurements from any combination of devices to be interlaced in the most convenient and expeditious fashion, ensuring that each estimate is computed from the most recent data offered by any combination of devices. The information from the various observations can then be blended using either a single SCAAT KF with multiple measurement models, or separate SCAAT filters (and thus statistics) each with single measurement models, in which case the estimates from the various models can be blended using</p>	

Exhibit E-21

CLAIM 6	Welch Thesis
	<p>a statistical multi-model approach (see for example [Bar-Shalom93]). Welch Thesis at 56-57.</p> <p><i>See also</i> Defendants' Invalidity Contentions for further discussion.</p>
<p>[6.a] enumerating sensing elements available to a tracking system that includes an estimation subsystem that estimates a position or orientation of an object; and</p>	<p>At least under Plaintiffs' apparent infringement theory, Welch Thesis discloses, either expressly or inherently, enumerating sensing elements available to a tracking system that includes an estimation subsystem that estimates a position or orientation of an object. In the alternative, this element would be obvious over Welch Thesis in light of the other references disclosed in Defendants' Invalidity Contentions and/or the knowledge of one of ordinary skill in the art.</p> <p><i>See, e.g.:</i></p> <p>A Kalman filter can be used to estimate a globally-observable process by sequentially incorporating only measurements of locally-unobservable processes. The use of a Kalman filter in such a manner offers several advantages: (1) a flexible framework for heterogeneous multisensor data fusion; (2) a unique opportunity to perform concurrent device autocalibration; and in a system that allows only sequential measurements, (3) significantly improved estimate rates and latencies; and (4) avoidance of the incorrect simultaneity assumption.</p> <p>Welch Thesis at 43.</p> <p>The Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) means of using noisy measurements to estimate the state of a linear system, while minimizing the expected mean-squared estimation error.</p> <p>Welch Thesis at 45.</p> <p>The SCAAT method represents an unusual approach to Kalman filter based multisensor data fusion. Because the filter operates on single sensor measurements, new estimates can be computed as soon as measurements from an individual sensor of any type become available, in virtually any order, and at any (possibly varying) rate. Such flexibility allows measurements from any combination of devices to be interlaced in the most convenient and expeditious fashion, ensuring that each estimate is computed from the most recent data offered by any combination of devices. The information from the various observations can then be blended using either a single SCAAT KF with multiple measurement models, or separate SCAAT filters (and thus</p>

Exhibit E-21

CLAIM 6	Welch Thesis
	<p>statistics) each with single measurement models, in which case the estimates from the various models can be blended using a statistical multi-model approach (see for example [Bar-Shalom93]). Welch Thesis at 56-57.</p> <p>For the sake of illustration, imagine an inertial-acoustical hybrid tracking system composed of three accelerometers, three rate gyros, and an acoustical line-of-sight system (to control drift from the inertial sensors). Note that not only will the acoustical measurements take longer than the inertial measurements, the acoustical measurement times will vary with distance between the source and sensors. A conventional method for data fusion might repeat the fixed pattern shown in figure 2.7. Notice that an estimate is produced only after collecting an orthogonal group of measurements from each (any one) subsystem.</p> <p>Figure 2.7: Timing diagram for a hypothetical conventional hybrid tracking system. The state estimate is updated only after each group of 3 homogeneous measurements.</p> <p>In contrast, a SCAAT implementation might interleave sensor measurements as depicted in figure 2.8. Note the flexibility of measurement type, availability, rate, and ordering. Again because an estimate is produced with every sensor measurement, latency is reduced and the estimation rate is increased.</p> <p>Figure 2.8: Timing diagram for a SCAAT inertial-acoustic hybrid tracking system. The state estimate is updated whenever an individual measurement becomes available.</p> <p>Welch Thesis at 57-58.</p>

Exhibit E-21

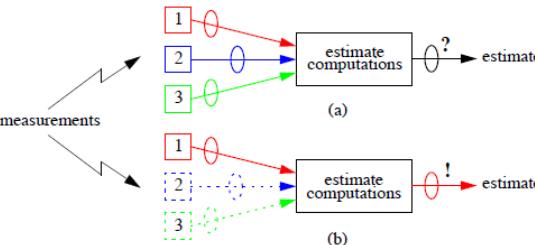
CLAIM 6	Welch Thesis
	<p>On the other hand, because the SCAAT method generates a new tracking estimate with each individual measurement, individual device imperfections are more readily identified. Furthermore, because the simultaneity assumption is avoided, the motion restrictions discussed in section 2.3.2 are removed, and autocalibration can be performed while concurrently tracking a target under normal conditions. The specific autocalibration method is presented in chapter 4, with experimental results in chapter 6.</p> <p>Welch Thesis at 61.</p>  <p>Figure 2.11: Autocalibration and attribution of measurement error. (a) Most algorithms operate on multiple measurements as a group, hence uncertainty or error (represented by the ellipses) in the final estimates is difficult to attribute to any individual sensor. (b) With the SCAAT method, uncertainty in final estimates can more easily be attributed to a particular individual sensor.</p> <p>Welch Thesis at 62.</p> <p>The tracking system that I employ in my experiments is an “inside-looking-out” optoelectronic system designed for interactive computer graphics or virtual environments. The system, which we call the “HiBall tracker”, is an improved version of the wide-area system described in [Ward92]. In these systems, user-mounted optical sensors observe infrared light-emitting diodes (LEDs) or beacons mounted in the ceiling above the user. The locations of the beacons are known (to some degree) so observations of them can be used to estimate the user’s position and orientation.</p> <p>Welch Thesis at 191.</p>

Exhibit E-21

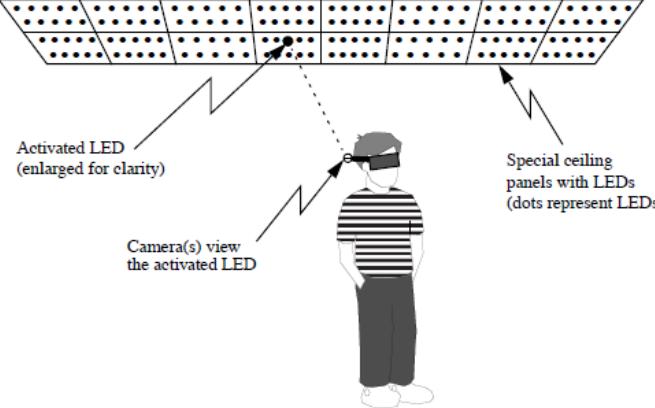
CLAIM 6	Welch Thesis
	 <p data-bbox="559 660 1214 742">Figure D.1: An outward-looking optoelectronic tracking system. User-mounted cameras look outward (generally upward) at active beacons in the environment.</p> <p data-bbox="517 758 792 791">Welch Thesis at 191.</p> <p data-bbox="517 824 1989 1052">One goal of the HiBall system is to provide a user with <i>wide-area</i> tracking. To this end, the LEDs are installed in special ceiling panels that replace standard-size acoustic ceiling tiles. (See figure D.1.) These tiles can be installed over a large area, thus providing a large working area. In fact, the current UNC installation consists of enough ceiling tiles to cover an area of approximately 5x5 meters, with a corresponding total of over 3,000 LEDs. The LED positions in world coordinates are initially estimated based on the ceiling panel design, which has them installed in a regular two-dimensional grid.</p> <p data-bbox="517 1085 1989 1232">The LEDs are connected to special circuit boards that are mounted on (above) the ceiling tiles, and these circuit boards are then connected to a computer. Thus LEDs can be individually activated under computer control as needed for the SCAAT observations. (The ceiling circuitry allows beacon activation at over 5000 LEDs per second.)</p> <p data-bbox="517 1232 792 1264">Welch Thesis at 192.</p> <p data-bbox="517 1297 1989 1411">In the original system described by [Ward92] the user wore a relatively large head-mounted mechanical fixture that supported several individually self-contained optical sensors or “cameras” and a backpack that contained the necessary signal processing and A/D conversion circuitry as shown in figure D.2.</p>

Exhibit E-21

CLAIM 6	Welch Thesis
	<p>In the new system the camera fixture and backpack in figure D.2 are together replaced by a relatively small sensor cluster called the HiBall. Figure D.3 is a picture of an unpopulated HiBall with a golf ball to convey a notion of size.</p> <p>A populated HiBall contains six lenses, six photodiodes with infrared filters, and all of the necessary circuitry for signal processing, A/D conversion, control, and high-speed serial communication. It is designed so that each photodiode can view infrared beacons (LEDs in this case) through each of several adjacent lenses, thus implementing up to 26 distinct infrared cameras.</p> <p>The photodiodes provide four signals that together indicate the position of the centroid of light (infrared in this case) as it appears on the two-dimensional photodiode surface. At any point in time, the internal A/D conversion circuitry can sample these signals for any one photodiode. These samples would then be sent to an external computer via a high-speed serial link where they would be converted to the measurement that reflect the position of the image of the infrared beacon on the two-dimensional photodiode.</p> <p>If the photodiode measurements are viewed as images of the ceiling beacons (known scene points), the HiBall tracker can be viewed as an implementation of the abstract image-based example initially introduced in section 1.2 on page 39 (see figures 1.4-1.6) and later used in chapter 5. Hence my frequent references to a HiBall lens and sensor pair as a camera.</p> <p>Welch Thesis at 192-93.</p> <p><i>See Disclosures with respect to 6.pre, supra; see also Defendants' Invalidity Contentions for further discussion.</i></p>
[6.b] providing parameters specific to the enumerated sensing elements to the tracking system to enable the estimation subsystem to be configured based on the parameters specific to the enumerated sensing elements to enable the	<p>At least under Plaintiffs' apparent infringement theory, Welch Thesis discloses, either expressly or inherently, providing parameters specific to the enumerated sensing elements to the tracking system to enable the estimation subsystem to be configured based on the parameters specific to the enumerated sensing elements to enable the estimation subsystem to estimate the position or orientation of the object. In the alternative, this element would be obvious over Welch Thesis in light of the other references disclosed in Defendants' Invalidity Contentions and/or the knowledge of one of ordinary skill in the art.</p> <p><i>See, e.g.:</i></p>

Exhibit E-21

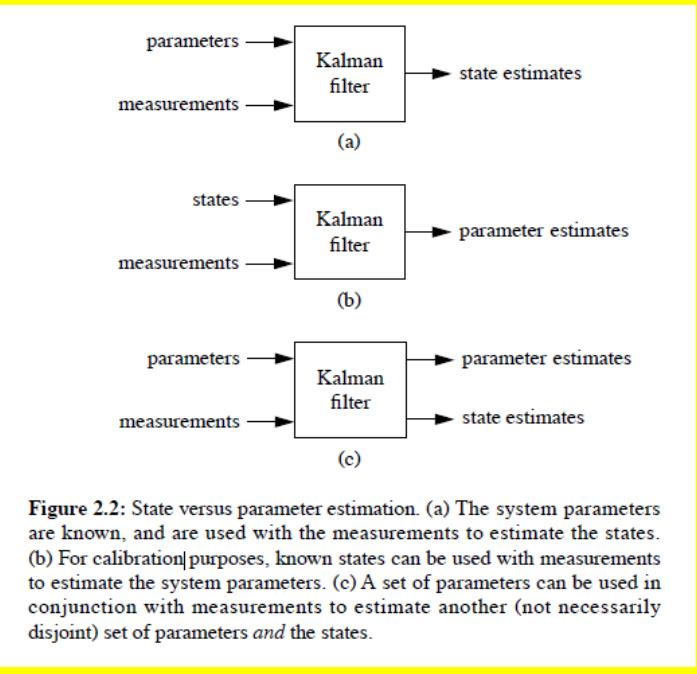
CLAIM 6	Welch Thesis
<p>estimation subsystem to estimate the position or orientation of the object.</p>	 <p>The diagram shows three configurations of a Kalman filter:</p> <ul style="list-style-type: none"> (a) A Kalman filter takes "parameters" and "measurements" as inputs and produces "state estimates". (b) A Kalman filter takes "states" and "measurements" as inputs and produces "parameter estimates". (c) A Kalman filter takes both "parameters" and "measurements" as inputs and produces both "parameter estimates" and "state estimates". <p>Figure 2.2: State versus parameter estimation. (a) The system parameters are known, and are used with the measurements to estimate the states. (b) For calibration purposes, known states can be used with measurements to estimate the system parameters. (c) A set of parameters can be used in conjunction with measurements to estimate another (not necessarily disjoint) set of parameters <i>and</i> the states.</p> <p>Welch Thesis at 49.</p>

Exhibit E-21

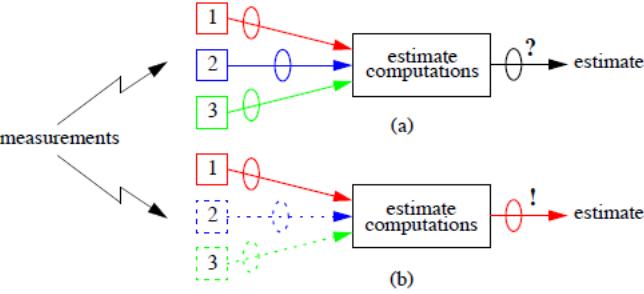
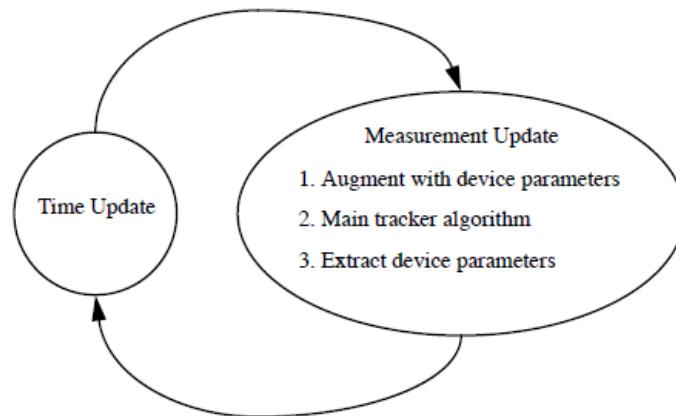
CLAIM 6	Welch Thesis
	 <p data-bbox="538 554 1182 701">Figure 2.11: Autocalibration and attribution of measurement error. (a) Most algorithms operate on multiple measurements as a group, hence uncertainty or error (represented by the ellipses) in the final estimates is difficult to attribute to any individual sensor. (b) With the SCAAT method, uncertainty in final estimates can more easily be attributed to a particular individual sensor.</p> <p data-bbox="517 709 770 742">Welch Thesis at 62.</p>  <p data-bbox="570 1215 1393 1313">Figure 4.12: The revised tracking algorithm for autocalibration. The time update consists of equation (4.14). The measurement update consists of equations (4.24)-(4.27), then (4.15)-(4.22), and finally equation (4.28).</p> <p data-bbox="517 1330 792 1362">Welch Thesis at 102.</p>

Exhibit E-21

CLAIM 6	Welch Thesis
	<p><i>See also</i> Welch Thesis Chapter 2.5 (describing autocalibration for sensor subsystems); Chapter 4.4 (autocalibration using SCAAT algorithm); Chapter 6.1 (describing autocalibration of HiBall sensor system using SCAAT)</p> <p><i>See</i> Disclosures with respect to Element 6.a, <i>supra</i>; <i>see also</i> Defendants' Invalidity Contentions for further discussion.</p>

F. DEPENDENT CLAIM 8

CLAIM 8	Welch Thesis
<p>[8] The method of claim 6 wherein the set of sensing elements comprises at least one sensor and at least one target, the sensor making a measurement with respect to the target.</p>	<p>At least under Plaintiffs' apparent infringement theory, Welch Thesis discloses, either expressly or inherently, the method of claim 6 wherein the set of sensing elements comprises at least one sensor and at least one target, the sensor making a measurement with respect to the target. In the alternative, this element would be obvious over Welch Thesis in light of the other references disclosed in Defendants' Invalidity Contentions and/or the knowledge of one of ordinary skill in the art.</p> <p><i>See, e.g.:</i></p> <p>The Kalman filter provides a powerful mathematical framework within which a minimum mean-square-error estimate of a user's position and orientation can be tracked using a sequence of single sensor observations, as opposed to groups of observations. We refer to this new approach as single-constraint-at-a-time or SCAAT tracking. The method improves accuracy by properly assimilating sequential observations, filtering sensor measurements, and by concurrently autocalibrating mechanical or electrical devices. The method facilitates user motion prediction, multisensor data fusion, and in systems where the observations are only available sequentially it provides estimates at a higher rate and with lower latency than a multiple-constraint approach.</p> <p>Welch Thesis at Abstract.</p> <p>Throughout this dissertation I refer to "sources", "sensors", or "devices", and it's particularly important to understand what I mean by these words not only to avoid confusion, but to understand the basic SCAAT approach. I use the words "source" or "sensor" to refer to the single (minimal) electrical or mechanical component used to excite or sense a particular physical medium. Using this nomenclature, some example</p>

Exhibit E-21

CLAIM 8	Welch Thesis
	<p>sources include a single-axis electromagnetic dipole, an infrared LED, and a single GPS satellite. Some example sensors include a single-axis electromagnetic coil, a single camera, and a GPS receiver. I will use the word “device” to refer to either a source or sensor. On the other hand, when I want to refer to a mechanical fixture that incorporates multiple sources or sensors, I will use phrases such as “source unit” or “sensing unit”.</p>
	<p>Welch Thesis at 35.</p>
	<p>A key point of this dissertation is that even incomplete observations provide some information, and that the partial information can be used incrementally to improve an existing estimate of the solution. As long as individual measurements are incomplete in complementary ways, they can be used together over time to progressively improve an existing estimate. Rather than attempting to compute precise closed-form estimates of points in state space, we can instead push the current state estimate along the track indicated by the most recent (incomplete) observation. By carefully blending an ongoing sequence of incomplete observations in this way, one can generate an improved state estimate with each new constraint (observation)—guiding the sequence of estimates along the target track, using a single constraint at a time.</p>
	<p>Welch Thesis at 42.</p>
	<p>In this dissertation I claim that there are significant benefits to using a Kalman filter in what I call a SCAAT fashion. But why use a Kalman filter in the first place? There are four typical reasons why people employ Kalman filters in systems where a signal (often continuous) is to be estimated with a sequence of discrete measurements or observations: (1) filtering; (2) data fusion; (3) prediction; and (4) calibration. In this section I briefly examine each of these in the context of tracking or navigation. Once I’ve argued that a Kalman filter is a good thing in general, I spend the remainder of the chapter explaining how the SCAAT approach uniquely and elegantly addresses these four issues as well as other concerns.</p>
	<p>Welch Thesis at 44.</p>
	<p>The use of a Kalman filter requires not only a dynamic model as described in section 4.2.1, but also a measurement model. The measurement model is used to predict the ideal noise-free response of each sensor and source pair, given the filter’s current estimate of the target state as in equations (4.2) and (4.3). The prediction is then compared with an actual measurement, and the results are used to generate a correction for the filter’ current estimate of the target state.</p>
	<p>Welch Thesis at 78.</p>

Exhibit E-21

CLAIM 8	Welch Thesis
	<p>In choosing the measurement elements to incorporate during a SCAAT Kalman filter measurement update one must consider the available sources and sensors as described in “Defining the Nomenclature” on page 35, and then identify the constraints and corresponding measurements that will be used to update the filter. Recall from “A Single Constraint” on page 37 that in the purest mathematical sense, a single constraint corresponds to one scalar equation describing a known relationship between the unknown state vector elements. Correspondingly a SCAAT Kalman filter should, in the purest sense, generate each new estimate with only a single scalar measurement from one source and sensor pair.</p> <p>Welch Thesis at 79.</p> <p>So given the preceding discussion, what criteria should one use when choosing the measurement elements or constraints to incorporate during a SCAAT Kalman filter measurement update? Given the complete set of available sources and sensors for the system, I suggest the following guidelines:</p> <ul style="list-style-type: none"> a. begin by identifying the set of all sensor and corresponding source elements that can possibly be observed at any one instant in time; b. within this set identify any single source and sensor pairs that should be isolated from the others; c. for each such pair identify the scalar elements yielded from a measurement of the sensor with the corresponding source; and d. apply these guidelines until all the available sources and sensors have been considered. <p>Welch Thesis at 80.</p> <p>Consider, for example, tracking two rigidly mounted 2D cameras that can observe four fixed beacons or scene points, as depicted for one camera in figure 1.4 on page 39. The combined use of two sensors (the 2D cameras) and four sources (the beacons) yields a total of 16 scalar measurement elements for the complete set of sources and sensors: a pair for each of four beacons as seen by each of two cameras. If the two cameras cannot be shuttered and scanned-out simultaneously then guideline (a) would reduce the original set to two new sets, each with one 2D camera and four beacons. If one is uncertain about the 3D locations of the beacons, and/or wishes to calibrate (estimate) the positions concurrently while tracking, then guideline (b) would break these two sets into eight sets, each with one 2D camera and one beacon. Finally, per guideline (c) one would note that the eight camera-beacon pairs each yield a image coordinate, i.e. scalar elements. If</p>

Exhibit E-21

CLAIM 8	Welch Thesis
	<p>there were more source and sensor types, one would repeat this process per guideline (d). Welch Thesis at 80-81.</p> <p>In light of the device isolation discussion in section 2.5.4 on page 61, the application of the above guidelines in the general case leads to the following heuristic for choosing the SCAAT Kalman filter measurement elements (constraints):</p> <p>During each SCAAT Kalman filter measurement update one should observe a single sensor and source pair only.</p> <p>Thus for the two-camera, four-beacon example, we could have immediately determined that each SCAAT Kalman filter measurement update should incorporate the image coordinate of one beacon as seen in one camera. Each such observation could in fact be considered a single geometric constraint: the intersection of a line, the line from the beacon to the principal point of the camera lens, and a plane, the image plane. Welch Thesis at 81.</p> <p>With respect to the SCAAT method, we have chosen to define a single constraint for the HiBall tracking system as one observation of one beacon with one HiBall lens and sensor pair. Thus the measurement vector given in equation (4.10) and the respective components in equations (4.11) and (4.12) are all two-dimensional, i.e. . The situation is similar to that depicted in figure 1.6 on page 41. Welch Thesis at 123.</p> <p>If the photodiode measurements are viewed as images of the ceiling beacons (known scene points), the HiBall tracker can be viewed as an implementation of the abstract image-based example initially introduced in section 1.2 on page 39 (see figures 1.4-1.6) and later used in chapter 5. Hence my frequent references to a HiBall lens and sensor pair as a camera. Welch Thesis at 193.</p> <p><i>See Disclosures with respect to Claim 6, <i>supra</i>; see also Defendants' Invalidity Contentions for further discussion.</i></p>

Exhibit E-21

G. DEPENDENT CLAIM 9

CLAIM 9	Welch Thesis
<p>[9] The method of claim 8 wherein the target comprises a natural feature in an environment.</p>	<p>At least under Plaintiffs' apparent infringement theory, Welch Thesis discloses, either expressly or inherently, the method of claim 8 wherein the target comprises a natural feature in an environment. In the alternative, this element would be obvious over Welch Thesis in light of the other references disclosed in Defendants' Invalidity Contentions and/or the knowledge of one of ordinary skill in the art.</p> <p><i>See, e.g.:</i></p> <p>The Kalman filter provides a powerful mathematical framework within which a minimum mean-square-error estimate of a user's position and orientation can be tracked using a sequence of single sensor observations, as opposed to groups of observations. We refer to this new approach as single-constraint-at-a-time or SCAAT tracking. The method improves accuracy by properly assimilating sequential observations, filtering sensor measurements, and by concurrently autocalibrating mechanical or electrical devices. The method facilitates user motion prediction, multisensor data fusion, and in systems where the observations are only available sequentially it provides estimates at a higher rate and with lower latency than a multiple-constraint approach.</p> <p>Welch Thesis at Abstract.</p> <p>A key point of this dissertation is that even incomplete observations provide some information, and that the partial information can be used incrementally to improve an existing estimate of the solution. As long as individual measurements are incomplete in complementary ways, they can be used together over time to progressively improve an existing estimate. Rather than attempting to compute precise closed-form estimates of points in state space, we can instead push the current state estimate along the track indicated by the most recent (incomplete) observation. By carefully blending an ongoing sequence of incomplete observations in this way, one can generate an improved state estimate with each new constraint (observation)—guiding the sequence of estimates along the target track, using a single constraint at a time.</p> <p>Welch Thesis at 42.</p> <p>In this dissertation I claim that there are significant benefits to using a Kalman filter in what I call a SCAAT fashion. But why use a Kalman filter in the first place? There are four typical reasons why people employ Kalman filters in systems where a signal (often continuous) is to be estimated with a sequence of discrete measurements or observations: (1) filtering; (2) data fusion; (3) prediction; and (4) calibration. In this section I</p>

Exhibit E-21

CLAIM 9	Welch Thesis
	<p>briefly examine each of these in the context of tracking or navigation. Once I've argued that a Kalman filter is a good thing in general, I spend the remainder of the chapter explaining how the SCAAT approach uniquely and elegantly addresses these four issues as well as other concerns.</p> <p>Welch Thesis at 44.</p> <p>The use of a Kalman filter requires not only a dynamic model as described in section 4.2.1, but also a measurement model. The measurement model is used to predict the ideal noise-free response of each sensor and source pair, given the filter's current estimate of the target state as in equations (4.2) and (4.3). The prediction is then compared with an actual measurement, and the results are used to generate a correction for the filter' current estimate of the target state.</p> <p>Welch Thesis at 78.</p> <p>In choosing the measurement elements to incorporate during a SCAAT Kalman filter measurement update one must consider the available sources and sensors as described in "Defining the Nomenclature" on page 35, and then identify the constraints and corresponding measurements that will be used to update the filter. Recall from "A Single Constraint" on page 37 that in the purest mathematical sense, a single constraint corresponds to one scalar equation describing a known relationship between the unknown state vector elements. Correspondingly a SCAAT Kalman filter should, in the purest sense, generate each new estimate with only a single scalar measurement from one source and sensor pair.</p> <p>Welch Thesis at 79.</p> <p>So given the preceding discussion, what criteria should one use when choosing the measurement elements or constraints to incorporate during a SCAAT Kalman filter measurement update? Given the complete set of available sources and sensors for the system, I suggest the following guidelines:</p> <ol style="list-style-type: none"> a. begin by identifying the set of all sensor and corresponding source elements that can possibly be observed at any one instant in time; b. within this set identify any single source and sensor pairs that should be isolated from the others; c. for each such pair identify the scalar elements yielded from a measurement of the sensor with the corresponding source; and

Exhibit E-21

CLAIM 9	Welch Thesis
	<p>d. apply these guidelines until all the available sources and sensors have been considered. Welch Thesis at 80.</p> <p>Consider, for example, tracking two rigidly mounted 2D cameras that can observe four fixed beacons or scene points, as depicted for one camera in figure 1.4 on page 39. The combined use of two sensors (the 2D cameras) and four sources (the beacons) yields a total of 16 scalar measurement elements for the complete set of sources and sensors: a pair for each of four beacons as seen by each of two cameras. If the two cameras cannot be shuttered and scanned-out simultaneously then guideline (a) would reduce the original set to two new sets, each with one 2D camera and four beacons. If one is uncertain about the 3D locations of the beacons, and/or wishes to calibrate (estimate) the positions concurrently while tracking, then guideline (b) would break these two sets into eight sets, each with one 2D camera and one beacon. Finally, per guideline (c) one would note that the eight camera-beacon pairs each yield a image coordinate, i.e. scalar elements. If there were more source and sensor types, one would repeat this process per guideline (d). Welch Thesis at 80-81.</p> <p>In light of the device isolation discussion in section 2.5.4 on page 61, the application of the above guidelines in the general case leads to the following heuristic for choosing the SCAAT Kalman filter measurement elements (constraints):</p> <p>During each SCAAT Kalman filter measurement update one should observe a single sensor and source pair only.</p> <p>Thus for the two-camera, four-beacon example, we could have immediately determined that each SCAAT Kalman filter measurement update should incorporate the image coordinate of one beacon as seen in one camera. Each such observation could in fact be considered a single geometric constraint: the intersection of a line, the line from the beacon to the principal point of the camera lens, and a plane, the image plane. Welch Thesis at 81.</p> <p>With respect to the SCAAT method, we have chosen to define a single constraint for the HiBall tracking system as one observation of one beacon with one HiBall lens and sensor pair. Thus the measurement vector given in equation (4.10) and the respective components in equations (4.11) and (4.12) are all two-dimensional, i.e. . The situation is similar to that depicted in figure 1.6 on page 41. Welch Thesis at 123.</p>

Exhibit E-21

CLAIM 9	Welch Thesis
	<i>See Disclosures with respect to Claim 8, supra; see also Defendants' Invalidity Contentions for further discussion.</i>